A Catalogue of Zeldovich Pancakes

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Abstract

Using the standard cold dark matter model ΛCDM, it is predicted that there will be small fluctuations in the primordial energy density. These fluctuations are expected to lead to a cosmic web [1] under the influence of gravity and time. This web will consist of dense galaxy clusters interlinked by less dense two-dimensional walls, so called Zeldovich pancakes [2], and one-dimensional filaments.

Galaxy clusters and filaments have been observed for a long time, but only recently have Zeldovich pancakes been observed outside of simulations [6]. The reason these have only recently been observed is because they are much less dense than filaments and clusters, to the point of being hard to differentiate from the average density of their environs [4,5]. Using the method we invented in Falco et. al [6] to find 2 pancakes as a basis, I create a fully automatic program capable of finding pancakes without human input, in galaxy cluster widely different from each other. I apply this program to the Abell galaxy clusters and using the SDSS catalogue I check for potential pancakes in the galaxy clusters. While most of the cluster are contained in the SDSS many of the clusters are only partially covered. I try to make the program compensate for this and manage to create the first catalogue of Zeldovich pancakes by finding 197 of them in 113 different clusters.

Using the data I gather I perform rudimentary tests on the method to check the boundaries and limits of what should be expected of it. I also display data for a few cases where I have found multiple pancakes in a single cluster.

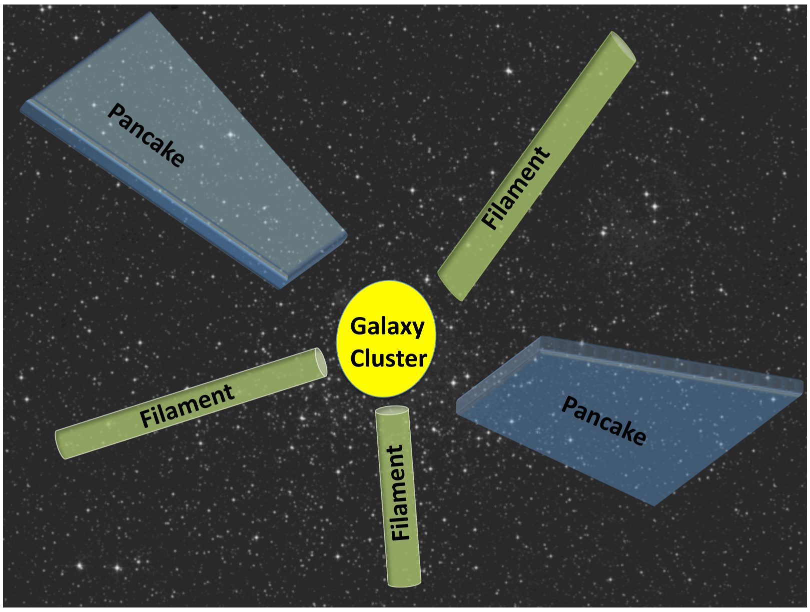

Figure 1: *Schematic figure of pancakes and filaments around a galaxy cluster. The figure is from Falco et al. [6].*

1 Theory

1.1 Structures in the Universe

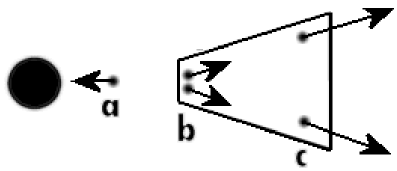

Figure 2: *Schematic figure showing the gravitational force from a galaxy cluster slowing down the Hubble flow of a pancake. At* ***a*** *the acceleration due to the gravitational force from the cluster exceeds that of the Hubble expansion. At* ***b*** *the Hubble expansion is slowed and at* ***c*** *the Hubble flow is nearly unimpeded.*

The most widely accepted model is currently the standard cosmological model, which I use for many assumptions and predictions. According to this model, the tiny perturbations in matter density in the very early universe, will decide how structures end up distributed and formed, under the influence of gravity [1]. This process assumes an early universe dominated by 3 dimensional distribution of matter which is nearly uniform in density. Under the influence of gravity, small perturbations in the density will then grow and accelerate the collapse. Due to this process accelerating as more matter collapse, it is expected that the 3 dimensional distribution will collapse in 1 dimension faster than the other dimensions. This results in flat structures or sheets called Zeldovich pancakes [2]. These sheets also have small perturbations, much like those found in the 3 dimensional distributions, which then cause the sheets to collapse further into 1 dimensional strings, or filaments. This process then continues to collapse the filaments into centralized regions of matter, compacts galaxies, or galaxy clusters depending on how much mass is contained in the region.

Assuming this picture to be true, one would expect a universe filled with clusters of galaxies which are interlinked or fed by filaments or pancakes (see Figure 1), which on scale of the universe looks much like the cosmic web seen from numerical simulations (see Figure 3). Unfortunately observing the cosmic web has proven very difficult, and as such filaments and especially pancakes have not been observed in great numbers unlike galaxies and galaxy clusters. This is mainly due to filaments and pancakes being far more diffuse than galaxies to the point of being difficult to distinguish from the average density of the universe [4,5]. Filaments have been identified on a few different occasions [3], pancakes however have only been identified a couple of times [6].

In conjunction with the paper by Falco et al. [6] and my supervisor Steen H. Hansen, I hy-

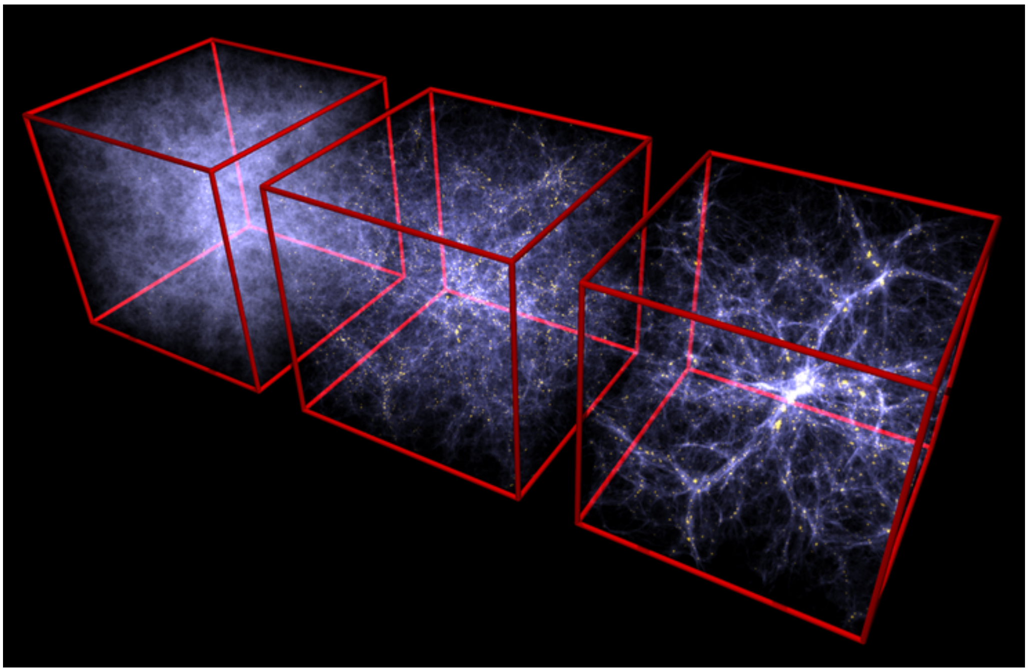

Figure 3: *Visualization of the cosmic web at $z = 6$, $z = 2$ and $z = 0$, from left to right. The figure is from the Millenium simulation using the GADGET-2 code, done by Springel et al. [7].*

pothesise that these pancakes should be clearly identifiable as overdensities at large virial radii in projected radius vs line of sight velocity (R,v_{los}) [6]. These overdensities should be regular and dense enough that a simple mathematical model should be able to identify them at a high success rate.

I will now explain in simple terms what I expect to see and how I want to use it to visually, that is through human observations, identify pancakes. There are simple geometrical structures with great spatial extent, located near galaxy clusters. The Hubble expansion will cause this structure to flow away from the galaxy cluster while the gravitational pull from the galaxy cluster will counteract this effect. The gravitational pull is stronger at smaller distances causing the parts of the structure closer to pancakes to be moving away from the cluster at a slower rate than parts of it that are further away from the centre of the cluster (see Figure 2). Using this I expect to be able to detect them in R,v_{los} as elongated, fairly thin structures of almost continuously distributed galaxies, with few or no holes. In reality I expect to see some clumping and in a few cases there might be complete galaxy groups as part of, or merged into the pancake. As I will show later these structures will typically be located at high distance from the galaxy cluster centre, stretching many Mpc, and several hundreds to a couple of thousand km/s.

1.2 Zeldovich pancakes

The pancakes I expect to find should not be confused with giant structures such as the Come Wall. These structures are 5 to 25 Mpc long and are located everywhere throughout space however the ones I detect are situated around galaxy clusters.

As Falco et al. [6] showed that using this method it is possible to detect pancakes at both positive and negative line of sight velocities when normalizing with the galaxy clusters centre as 0. The only determining factor being if the pancakes is closer or farther away from the galaxy cluster relative to us, with pancakes further away resulting in positive line of sight velocities and pancakes closer to us resulting in negative line of sight velocities.

Depending on the angle of the actual radius (r) to the pancake on the projected radius (R), which we can observe (see Figure 8). Depending on this angle I expect to see different inclinations of the pancakes in the R,v_{los} space. The method I am using is most sensitive to pancakes in the ± 20 to 70 degrees region. Pancakes outside this region will be hard to make out, since we cannot observe in the z direction and therefore have to infer their position from line of sight velocity which is not as accurate. This results in pancakes at very low angles to get lost in the noise around $v_{los} = 0$ in the R,v_{los} space whereas pancakes with high angles have too much inclination and therefore no extent in the R direction which makes them appear as galaxy groups or random structures at large angles. Even if these pancakes are identified it is hard to gain much information from them since for high angle pancakes varying the point at which their projection hits $v_{los} = 0$ by a small amount has a large effect on the calculated virial radii and for pancakes with small angles that point has a large uncertainty.

The orientation towards us also plays a role on how well the program is able to detect the pancakes. Pancakes which are edge on towards us are very difficult to detect since their length along the line of sight will cause a large increase in the velocity dispersion. This means that while the pancake on the sky will look very dense, for the program which looks at (R, v_{los}), the pancake will look like any other region. On the other hand, pancakes which have its flat side towards us will not look any different on the sky, but look very dense in (R, v_{los})

When looking in the right ascension vs declination space, I would expect to see some cases where the pancakes I find is dominated by the selection method, where I am looking at slices or cones (see Figure 10) of the whole cluster at a time. The effect this has is that pancakes will sometimes look like they are confined in the slices as the addition of a few more galaxies at the cost of including another slice is often not improving the results.
The program does however tries to optimize the pancakes independent of the number of slices used so I expect to only see the pancakes as cone shaped in cases where there is a lot of noise to the point where the signal to noise ratio decreases by including all the slices that contains part of the pancake.

In this work I will try to identify as many pancakes as I can in Abell galaxy clusters to create a pancake catalogue. A constraint to this is that I will be using the which does not contain all the clusters and in some cases does not have complete information on them. In cases where the information is incomplete the method will have a harder time identifying potential pancakes where the pancake and its environs are not completely covered by the SDSS.

1.2.1 Pancake velocity dispersion

Due to how they are formed it is expected that Zeldovich pancakes are cold, coherent structures with well defined and contained flows away from the galaxy cluster caused by the Hubble flow. By calculating the velocity dispersion of a pancake, we can get a measure of the coldness and coherence of the pancake [6]. Typically the velocity dispersion of pancakes will be around 100 to 200 km/s for pancakes which is much smaller than the 300 to 400 km/s I expect from filaments and galaxy groups [21]. This means I can use this measurement to identify pancakes and differentiate them from other structures that might otherwise look like pancakes [20].

1.3 7 sample pancakes

Since this is very new ground I will start by giving some examples of what I have found to better explain what is going on. I will here present 7 examples of pancakes I have found. Of them there are 2 close to ideal pancakes, and 5 pancakes with various concerns although they are still clearly pancakes. For some of these pancakes it is it looks like parts of them are not included although it seems they should have been. This is the result of the program trying many different thresholds for identifying overdensities and then picking the threshold that causes the least dispersion as explained in section 2.1.

Pancake 1 of Abell 858 - Seen in Figure 4. This pancake is one of the example of a close to ideal pancake. It show weak signs of some clumping around 18 Mpc projected radii, and a bit fewer galaxies than anywhere else at 20 Mpc. Beside this it is at an almost constant width and very long for its width. Beside this it should be noted that I expect to detect pancakes with an angle, between its real and projected radii, of 20 to 70 degree and this pancake is in the middle of that angle region. This makes it easier to pick out from the background and to further improve on this it is also a good deal away from $v = 0$ except for its innermost part but this goes for only few of the galaxies compared to the rest of the galaxies in the pancake.

Pancake 2 of Abell 1890 - Seen in Figure 5. This pancake is much larger and longer than the first example. It also shows some signs of clumping around 22 Mpc but it is only weakly. It should be noted that this clumping is close to $v = 0$ which means that there is a higher chance

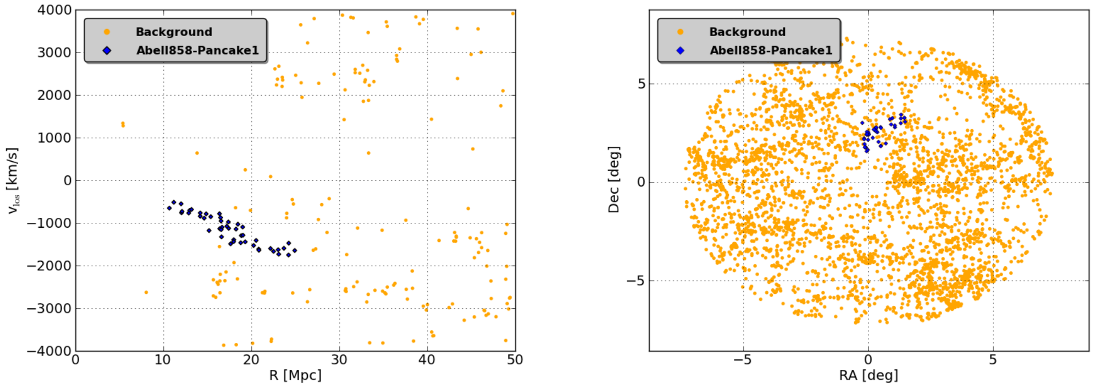

Figure 4: *Left: A fairly regular pancake with most of the characteristics I would expect. It does show some signs of fragmentation around 20 Mpc in projected radii and is slightly more clumped in just before compared to the rest. Besides this pancake's real orientation has an angle of about -47 degree to its projected radius, which places it in the middle of the best detection zone, is mostly away from the $v = 0$ region, and is fairly long and well ordered. All these factors makes it a pancake as close to textbook as I expect to get from observations. Right: How we would observe the pancake found in Abell 858 on the sky. As can clearly be seen there is no clear correlation between galaxies in the pancake based on their position in (RA,Dec). This reinforces the idea that this is indeed a pancake like the*

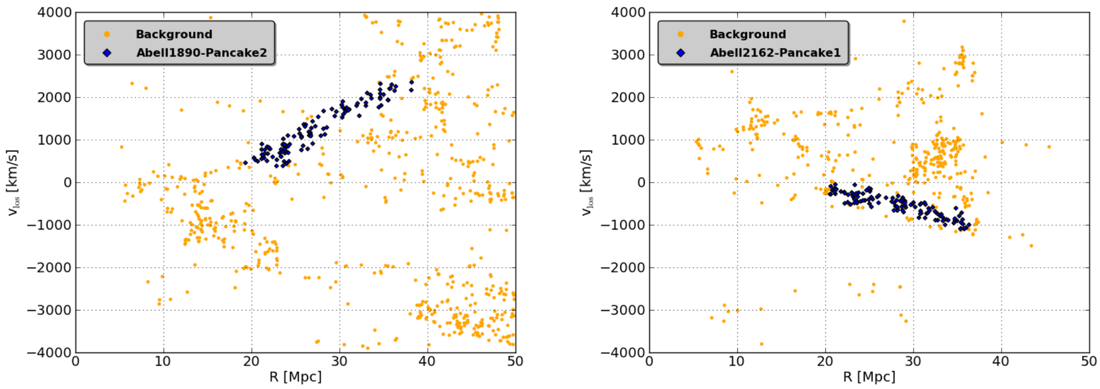

Figure 5: *Left: Another very typical pancake. Compared to the one from Abell 858 this one is much more dense. It does some signs of clumping in the innermost part which is to be expected since that part is close to $v = 0$. Right: A very dense pancake located close to $v = 0$. despite it being located so close to $v = 0$ it has a very low dispersion despite being in this location, which makes it an obvious pancake. It should be noted that is very clumpy which is most likely caused by the large amount of random overdensities around $v = 0$. Beside this it has a length I would expect of most pancakes and an angle to its projected radius of about 29 degrees placing it very close to the limit of what I expect the program to be able to find.*

for random galaxies around that part of the pancake. Other than that the pancake's galaxies are somewhat uniformly distributed, with an almost constant width that only gets a bit smaller at the far end. Its angle is at 51 degrees relative to its projected radius.

Pancake 1 of Abell 2162 - Seen in Figure 5. This pancake is located almost exclusively in the $v = 0$ region since it has a 29 degrees angle with its projected radius. While it never actually reaches or crosses $v = 0$ I do expect an increase in random galaxies around the pancake. This should have the effect of increasing its dispersion and clumpiness, which makes it harder to make a proper fit to. While I do see some clumping around 24 and 28 Mpc, there is no evidence of a much increased dispersion making it a very well behaved pancake. This means that it is recognized as a pancake even though the limits on dispersion is tightened for pancake in this region.

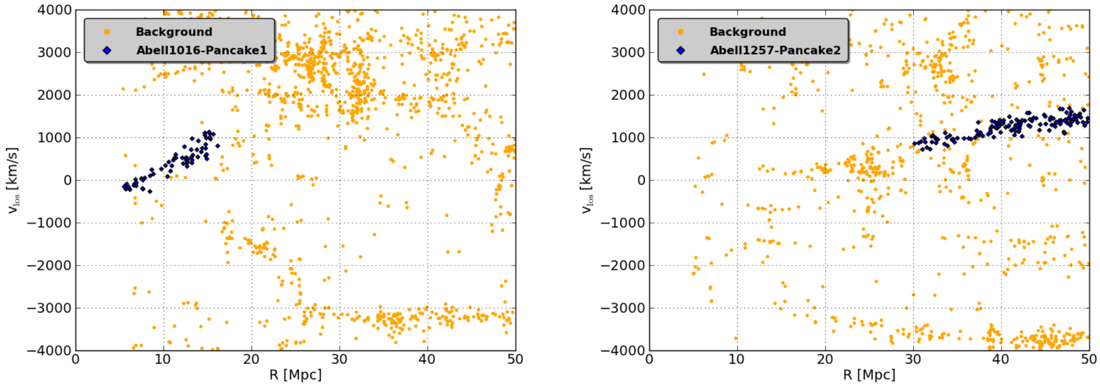

Figure 6: *Left: A slightly shorter than average pancake which crosses $v = 0$ around 7 Mpc. This means that part of it is drifting towards the galaxy cluster with most of it drifting away. This behaviour could explain the low density around 9 Mpc as the pancake seems to have a somewhat even but dense distribution of pancakes from 10 to 16 Mpc. There is of cause a chance that the part from 5 to 10 Mpc is just a random trail of galaxies but I have no convincing reason to manually cut that part away from the pancake. The pancake is located an at angle of about 51 degrees which makes it quite easy to spot for the program. Right: A large, dense pancake which shows signs of heavy clumping. There are very obvious clumps around 40 Mpc, 48 Mpc, and to a lesser degree 33 Mpc. The clump at 33 Mpc could be argued to be how dense the pancake would be if there has been no clumps. This would seem to be the case based on the region between the two clumps at 40 and 48 Mpc. The pancake does however seem quite sparse in the region between the two clumps at 33 and 40 Mpc. Based on this I have no good way to determine if the clump at 33 Mpc is in fact a clump. Besides this it has an angle of 24 degrees putting it very close what is possible for the program to detect. However since it reaches from 30 to 50 Mpc it mostly avoids the $v = 0$ region making it a lot easier to analyse. It should be noted that since I only use data up to 50 Mpc away from the cluster this pancake might be longer than what the program has recorded.*

Pancake 1 of Abell 1016 - Seen in Figure 6. This pancake has a large angle of about 51 degrees making it easy to spot, but it crosses the $v = 0$ region meaning there several unusual things regarding this pancake. Since it mostly is within the $v = 0$ region I expect it to have increased dispersion making it harder to fit. I also expect some amount of clumping inside the pancakes. I do see a large amount of clumpiness most places in the pancake as the inner half of the pancake also displays a higher dispersion than I would normally expect, taking the number of pancakes in the region into account. Due to it the pancake crossing $v = 0$ the innermost part of it drifts towards the galaxy cluster whereas the outermost part does not. This might be what has caused the low density around 9 Mpc. Another reason for the low density region could be that it is an extended random structure in the area. This would however not explain why it lines up so well with the rest of the pancake and I therefore argue that it is indeed part of the pancake.

Pancake 2 of Abell 1257 - Seen in Figure 6. With 137 member galaxies this pancake is very rich in galaxies. 3 clumps are easily identified in the pancake located at 33 Mpc, 40 Mpc, and 48 Mpc. The last two being the most obvious and the clump at 33 Mpc possible only looking like a clump due to the sparse region just before it. This is made more likely if the region between the clumps at 40 Mpc and 48 Mpc is what is assumed to be the normal density of the pancake. It should however be noted that if those two clumps indeed are small structures then it would be very likely that they share some galaxies between them, increasing the galaxy density in that region. To gain further confirmation that this is indeed a pancake I could look beyond 50 Mpc from the cluster. I do however want to stay consistent so for this paper I will not look for that. The pancake's angle to its projected radius is however 24 degrees, which puts it barely inside the region I expect to find pancakes in. In this case it is not as big a concern as it could have been however since the pancake is positioned so far away from the cluster that even a shallow angle puts it above the $v = 0$ region.

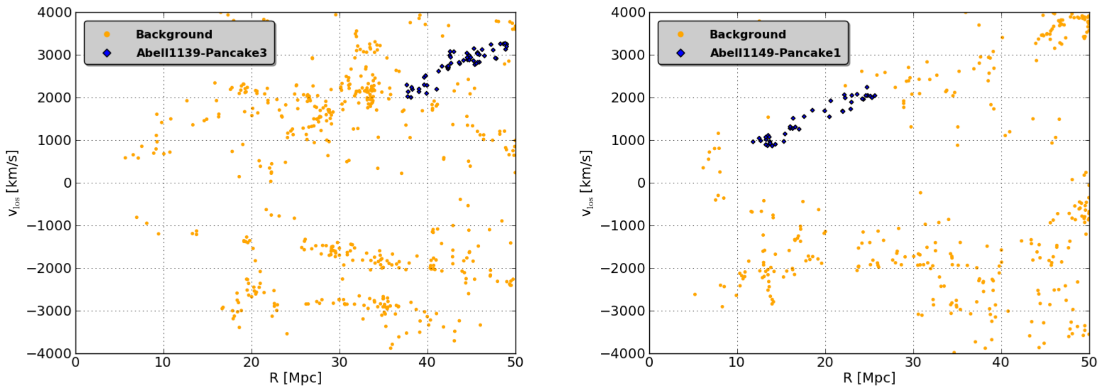

Figure 7: *Left: A sparse smaller than average pancake. Like pancake 2 from Abell 1257 it shows signs of clumping around 46 Mpc. Due to the combination of clumpiness in that very confined area and the pancake generally being sparse, the pancake is dominated by that clump. It is concerning that there are almost no galaxies around 42 Mpc which could mean that this is in fact not a pancake but two galaxy groups located at 39 and 46 Mpc. This is made more likely due to the large distance from the galaxy centre resulting in a weaker influence from it. Like pancake 2 from Abell 1257 it could very well be longer than what is seen here due to me only using data from within 50 Mpc of the cluster. Right: This pancake is very sparse. Besides the small clump at the innermost tip its galaxies somewhat evenly distributed along its length. Furthermore its width is almost constant. This combined with the 51 degree angle relative to its projected radius makes it almost a perfect pancake.*

Pancake 3 of Abell 1139 - Seen in Figure 7. This pancake is much more sparse than the others previously shown.It does however show signs of some clumping around 46 Mpc. It is a concern that the pancake is partly dominated by this clump when looking at number of pancakes. Due to this combined with the sparse structure means that if the clump has higher or lower line of sight velocity than the rest of the pancake fitting the pancake would lead to high uncertainties. Fortunately the pancake is almost at the centre of the pancake meaning that the pancake is not disrupted too much by the cluster, making it possible to use for extracting data bon the cluster. It is still a concern that there are very few galaxies around 42 Mpc making the structure look like there is a clump at 39 Mpc and one again at 46 Mpc. The fact that the pancake is far away from the cluster makes this more likely due to the weaker influence far away from the cluster where more random structures are to be expected. However the pancake still has the shape I expect and a dispersion within the range of expectation, which is far less than what I expect from galaxy groups. Based on this I argue that it is indeed a pancake. It should also be noted that like pancake 2 from Abell 1257 it can be longer than what is shown here since I only include data within 50 Mpc of the galaxy cluster.

Pancake 1 of Abell 1149 - Seen in Figure 7. This is the most sparse of the pancakes I will show here. Despite being quite sparse it is quite long and its galaxies are somewhat evenly distributed along its length. It does however have a clump at the innermost tip and since the rest of the pancake is quite sparse that clump will have a large effect on any fit of the pancake. It should be noted that the clump is around $v = 1000$ which is where I expect to begin to see random structures from the $v = 0$ region. This means that the clump might not actually be part of the pancake but is instead just random galaxies in same area.

1.4 Virial radius, mass and velocity

Throughout this paper I frequently use the terms virial radius, virial mass and virial velocity.

The virial radius, r_v, is given by the radius of a sphere centred on a galaxy cluster, within which the matter is in dynamical equilibrium. As this radius is difficult to determine observationally, we define the virial radius as the radius within which the mean density is Δ times the critical density, ρ_c. As such the virial mass is given by:

$$M_v = \frac{4}{3}\pi r_v^3 \Delta \rho_c \tag{1}$$

Where

$$\rho_c = \frac{3H}{8\pi G} \tag{2}$$

The rotational velocity at the virial radius is given by:

$$V_{vir}^2 = \frac{GM_v}{r_v} \tag{3}$$

1.5 Galaxy clusters

Galaxy clusters, like the local cluster, typically contain several hundred member galaxies, and their virial masses range from $10^{14} M_\odot$ to $10^{15} M_\odot$ within one virial radius. The virial radii varies a lot, but is typically in the range 1-3 Mpc making galaxy clusters the largest and heaviest gravitationally bound structures in the universe. The mass of galaxy clusters are mostly located near the centre, but a large portion of the mass is found outside the one virial radii in the cluster environs. It is in this region that I look for pancakes. These pancakes while large, are typically much more massive than their surroundings due to the dark matter they contain. To be certain that I stay within this region I only use data 5 to 50 Mpc from the galaxy cluster. Within 5 Mpc the galaxy cluster might dominate the flow and outside 50 Mpc the influence from the cluster might be overshadowed by other structures. The velocities of galaxies in clusters typically extend to around ± 1000 km/s, within one virial radii. In the nearby environment where I look for pancakes the Hubble flow increases the velocities and seeing galaxies moving at several thousand km/s relative to the cluster is not unusual. The pancakes I look for are also subject to the hubble flow and therefore they can have similar velocities.

1.5.1 Galaxy cluster mass estimation

Any pancakes I find can be used to estimate the virial radii, and therefore also the virial mass, of the galaxy cluster. To do this I use the universal infall velocity profile [6] which I fit to the observed velocities and radii of the data points that make up the pancake.

In the nearby environs of a galaxy cluster there is an infall scenario, where the gravitational pull from the mass of the cluster causes matter within a few virial radii to fall towards the cluster centre. Far from the galaxy cluster, the average motion is dominated by the Hubble flow causing galaxies to move away from the cluster. Between these scenarios, it is expected that there is a transition region where galaxies are significantly affected by both mechanisms. The Hubble flow in this region will still be stronger but the gravitational pull from the cluster still have a large enough effect that the radial movement is significantly slowed down.

As such, the total mean radial velocity of galaxies in this transition region is a combination of the two effects [6]:

$$\bar{v}_r = Hr + \bar{v}_p \tag{4}$$

Where Hr is the term coming from the Hubble expansion and $\bar{v}_p(r)$ is the negative mean infall velocity term due to the gravitational pull from the cluster mass.

The mean infall velocity term depends on the virial mass, M_v, of the galaxy cluster, as the gravitational pull will be greater for more massive galaxy clusters. As such, with knowledge of the radial velocity profile, we can estimate the mass of galaxy clusters [8].

1.5.2 Radial infall velocity profile

By fitting the radial mean velocity profile of galaxy cluster halos from cosmological numerical simulations in the interval from 3 to 8 virial radii, Falco et al. found the functional form of the infall velocity term in this region to be [6]:

$$\bar{v}_p \approx -v_0 \left(\frac{r}{r_v}\right)^{-b} \tag{5}$$

Where $v_0 = aV_{vir}$, $a = 0.8$ and $b = 0.42$.

If we combine equations (4) and (5) we obtain:

$$\bar{v}_r = Hr - aV_{vir} \left(\frac{r}{r_v}\right)^{-b} \tag{6}$$

1.5.3 Line of sight velocity profile

In order to use what can be observed to estimate the mass of galaxy cluster, I need a way to relate the three dimensional radius and velocity to what we are able to observe, that is the two dimensional projected radius and the line of sight velocity (see Figure 8).

The relation between the actual radius and the projected radius is given by:

$$R = r \cos\alpha \tag{7}$$

Where α is the angle between the actual radius, r, and the projected radius, R. The relation between the actual velocity and the line of sight velocity is given by:

$$v_{los} = v_r \sin\alpha \tag{8}$$

Combining equations (6), (7) and (8), we obtain the line of sight velocity profile [6]:

$$v_{los} = \sin\alpha \left[\frac{H_0 R}{\cos\alpha} - aV_{vir} \left(\frac{R}{r_v \cos\alpha} \right)^{-b} \right] \tag{9}$$

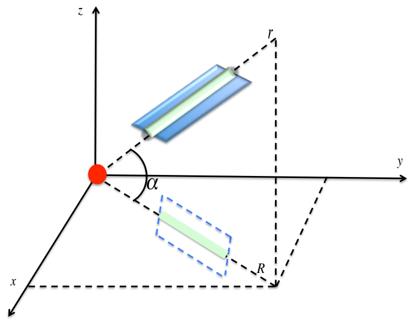

Figure 8: *Schematic figure showing a pancake along the actual radius, r, and the same pancake as seen by us along the projected radius, R, with the observer located far along the z axis. The figure is from Falco et al. [6].*

Setting $\Delta = H_0 D$ and combining equations (1), (2) and (3) we get an expression for the virial radius:

$$r_v = V_{vir} \sqrt{\frac{2}{D}} H_0^{-1} \tag{10}$$

Inserting this into equation (9) we obtain:

$$v_{los} = \sin\alpha \left[\frac{H_0 R}{\cos\alpha} - aV_{vir} \left(\sqrt{\frac{2}{D}} \frac{V_{vir} \cos\alpha}{H_0 R} \right)^{b} \right] \tag{11}$$

Where $D = 100$ is a constant.

Fitting any identified pancakes in the R,v_{los} space with this profile, called the universal infall velocity profile [6], it is possible to obtain estimates for the fitting parameters: The angle between the radius and projected radius, α, and the virial velocity of the galaxy cluster, V_{vir}.

Due to a multitude of methods that can estimate the mass of any clusters identified pancakes belong to this estimation can be used as a check to see if a potential pancake instead is a random structure. My program does use a check like this, but since I want it to be able to identify pancakes in highly irregular clusters, where it is difficult to identify the mass through other means, I have elected to not make it cross check with other data, but instead just check if the estimated mass is within reasonable bounds.

1.6 Data

The data on galaxies I use are taken from the Sloan Digital Sky Survey Data Release 10 (SDSS DR10) [10], but I only use the data from $z = 0$ to $z = 3.0$ as I do not look at galaxy cluster further away than $z = 2.0$. The reason I only use a single catalogue is to reduce the errors that might arise from using different instruments, or the surveys being done at different times. These factors are not necessarily large enough to limit future use multiple data sets to create other catalogues, but since this to my knowledge this catalogue will be the first of its kind to use this method I value precision over size so it is easier to evaluate the value of possible future catalogues.

I also use both the northern and southern Abell catalogues together with the supplementary southern clusters catalogue to obtain information on the galaxy clusters. I use this data to determine where the centres of the galaxy clusters are located and distance from us which I then use together with the Hubble constant to calculate how large an area in RA,Dec I should include to get around 40-50 Mpc in radius from the centre. The last part is mainly done to save time and avoid having the program search for pancakes hundreds of Mpc away from the cluster. I do a similar restraint for velocity where I only take data within ±4000 km/s from the centre of the cluster.

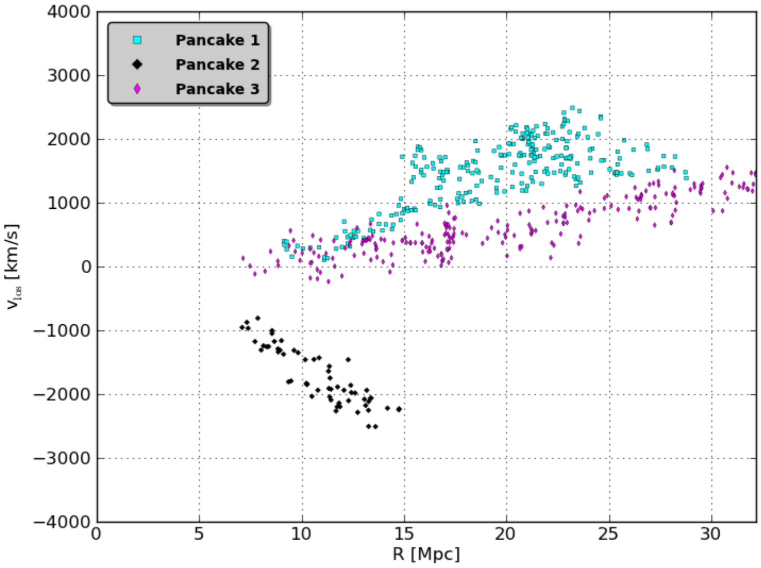

Figure 9: *The three pancakes identified near Coma, using the methods outlined in this section. While two of the pancakes appear near one another in this plot, all of them are located in different parts on the sky, which will be shown later.*

2 Methods

I take several steps to identify pancakes. The first step I take is identifying any coherent structure. I then check if these structures have characteristics I expect of pancakes.

In the first part of this section I will explain the steps I have to take for finding pancakes manually to give some insight in the method. If I only had to find pancakes for a single cluster the manual approach is efficient enough as it would be very easy to eliminate most of the structures, so I only have to check 1 or two candidates, but since I am creating a catalogue I have to fully automatize the process. This requires extra restraints and more careful adjustments of those restraints to get all the potential pancakes while not getting any false positives.

2.1 Manuel pancake selection

As stated in section 1.1, the method is made to locate pancakes near a chosen galaxy cluster. In table 1 I have summarized the method for doing so and I will use this section to go trough the process step by step. In figure 9 I have plotted 3 pancake candidates found by manually searching Abell 1656 (The Coma Cluster), as an example of the end results I expect to see.

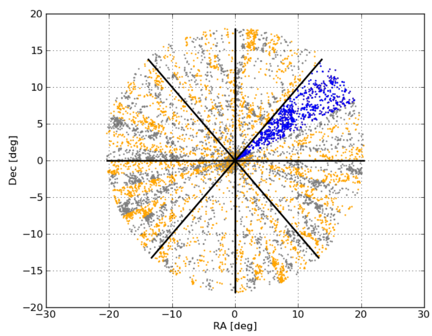

Figure 10: *The division of a galaxy cluster and its environs into 64 small slices (gray and orange), 8 larger slices (separated by black lines) and a sample signal cone in blue consisting of four small slices.*

a) Division of data into cones. To make the data more manageable the method starts by dividing the data into slices centred on the cluster in the right ascension vs declination space. This is done to make potential pancakes stand out clearly with a minimal amount of noise and to avoid having multiple pancakes or groups located in the same area in the R,v_{los} space. The number of slices needs to be small enough so that only the parts of the cluster

that contains a pancakes is selected when trying to identify them. There are however no limitation on how small a slice can be so the method will typically use 64 slices or more (see Figure 10). For my program I use 64 to stay consistent with Falco et al. [6]
In order to avoid cutting the pancakes into small bits several slices are looked at, at a time. After an area has been searched the next area is selected in such a way that it has a significant amount of overlap so that any pancakes which was only partly contained in the previous area can be found now.
To check if there are any pancakes in an area the method looks for structures in the radius vs line of sight (R,v_{los}) space. This is done by identifying areas with above average density of galaxies and then mapping out any continuous structures formed by these overdensities.

Table 1: Summary of steps taken to identify pancakes.

Step	Description	Figure
a)	Division of data into cones.	10
b)	Define overdensity threshold: Create random dataset, calculate mean and standard deviation of the number of data points within circles.	?? (left)
c)	Compare number of data points within circles to overdensity threshold and keep data points above this value.	?? (right)
d)	Select the pancake from the remains.	13 (left)
e)	Include data along the edges of the pancake.	13 (right)
f)	Reduce number of slices, if possible, and run analysis again.	

b) Finding overdensity thresholds.
The method then creates several thresholds to compare the density in in (R,v_{los}) of the selected region to. To do this it combines all the slices that are far enough away from the selected area that any pancakes partly inside the selected area will not be included in the combined slices. The combined slices then form a background region which is used to compare the areas that are currently being analysed for pancakes (see Figure 11). This process continues for every set of slices thus creating several backgrounds. In my program I define the background region as all slices except the signal region and 4 adjacent slices on each side of the signal region. All of the data set is not used since any pancakes in the cluster might create a higher density than normal in the area where they are located. This then causes some pancakes to not be picked up even though should have been.

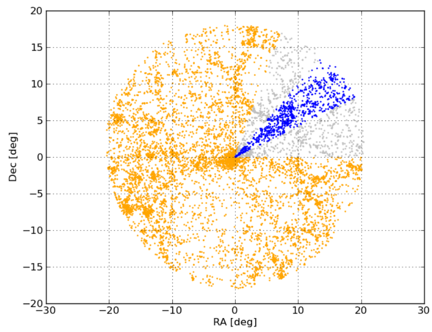

Figure 11: *The figure shows the background in orange, the four discarded slices on each side in grey and the slices in which the pancake is located in blue.*

After having created the background, I check how many of the galaxies have 1 neighbour, 2 neighbours and so on. I define a neighbour as being within a circle centred on the galaxy in question and with radius 300 km/s in (R, v_{los}), where I convert Mpc to km/s using the Hubble constant.

After this I normalize the number of neighbour galaxies each galaxy has by dividing with the total number of slices and multiply by the number of slices where I currently am looking for a pancake. The result is a distribution of nearby galaxies (see Figure 12) which several statistical values from which I get my thresholds. For my program these values are set 1σ, 1.3σ, 1.6σ, 2σ,

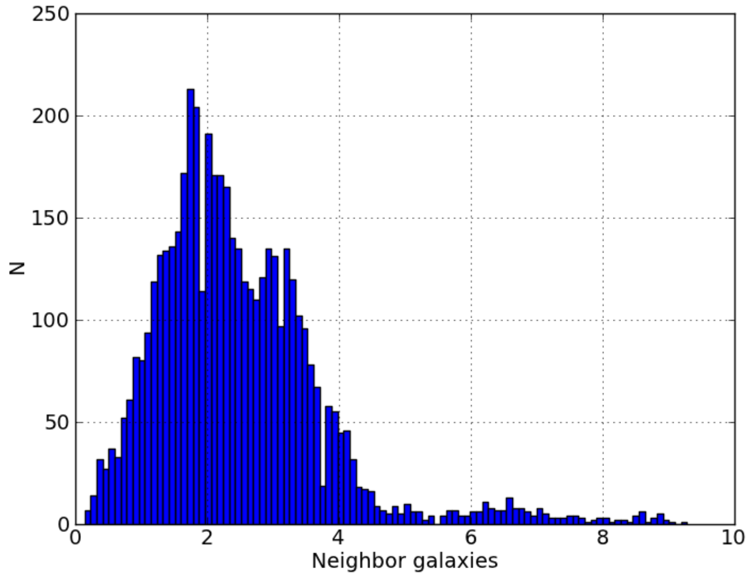

Figure 12: *The distribution of neighbour galaxies after being normalized to look after pancakes in 3 slices out of 64 total slices. This means that a count where I find 64 neighbours will get normalized to finding 3 neighbours here. While most of the counts are positioned before 4 neighbour galaxies I mainly use the tail beyond those 4 to create thresholds.*

2.6σ of the distribution. After calculating the number of neighbour pancakes at the different σ values I subtract the median of the distribution to get my thresholds.

In the case of Abell 695 which I used for figure 12 I the values 3.46875, 3.84375, 4.546875, 6.5625, and 8.34375 at the σ values and the median of the distribution at 2.203125. I then end up having 1.265625, 1.640625, 2.34375, 4.359375, and 6.140625 as my thresholds. Since galaxies cannot have partial neighbours this means that the first two thresholds are in fact identical while the rest are each different from each other. To improve my chances at detecting pancakes in dense regions such as the $v = 0$ region I then add 4 more thresholds which are at 1.25, 1.5, 2.0, and 2.5 times the largest threshold which for Abell 695 is 6.140625.

The reason I first calculate the benchmarks and then subtract the median instead of putting the benchmarks lower, is to get more reliable results since even if the distribution changes dramatically it will always have a trail of high number of neighbour galaxies which is what I mostly use to create these benchmarks.

Every galaxy in the signal region is then compared to these thresholds and if a galaxy has more nearby galaxies than the threshold that galaxy is considered to be part of a dense region for that specific threshold. Typically the thresholds are between 0.5 to 2 times the upper 2σ value of the background number density distribution. In my program I have 9 different thresholds with most of them being focused on differentiating very dense regions. The reason I do this is because pancakes that can be found at very lew thresholds are either very regular with little to no noise around them or they are highly irregular with possible galaxy groups being nested in them. In the case of the irregular pancakes, especially if a group is halfway nested into them, it is sometimes possible to find a sweet spot threshold where a potential group and other noise is almost completely removed, but these sweet spots are almost always at very high thresholds, which makes multiple high thresholds relevant for finding many pancakes.
It is possible to generate a random background and gain threshold values from it to save time, but using part of the cluster means that I do not have to account for rescaling due to number of data points or other characteristics unique to different galaxy cluster such as gravitational pull from nearby structures.

c) Compare data with with overdensity threshold. After having created the thresholds from the background, sets of 4 slices are examined. In this process the method removes all galaxies

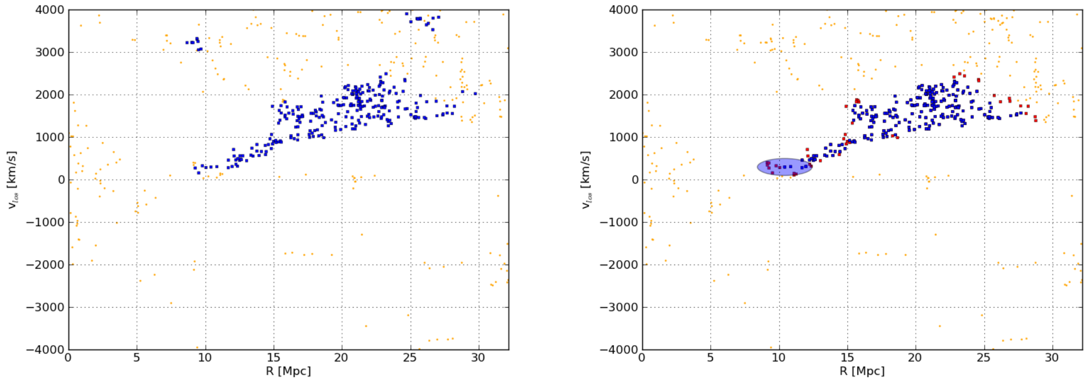

Figure 13: *Left: Typical remains after selecting overdensities, where the background of the cone in which the pancake is located is shown as orange circles and the overdensities are shown as blue squares. Right: A pancake and an ellipse of the type used to include data points along the edges of the pancake. The orange circles once again indicate the background, the blue squares indicate the pancake before inclusion of data along the edges of the pancake and the red squares indicate the data included along the edges.*

with less neighbours than the threshold. The end result then leaves several rough structures and in case there is a pancake like structure it is very easy to spot as its shape is different than the shape of most random structures (see Figure 13 left). To ensure that no pancake is missed the next region contains some of the slices of the previous region. This means that only 1 or 2 new slices are used with the rest of the slices being from the previous region.

d) Select pancake from the overdense structures. At this point I use a friends of friends algorithm, which I wrote together with Thejs Brinckmann for our bachelor's thesis, to check which galaxies are part of the same structure in (R,v_{los}). The maximum allowed distance between two galaxies for them to be considered part of the same structure is set to $1900/(n)^{0.25}$, where n is the total number of galaxies in the dataset for the cluster I am examining. The number is found through empirical analysis using the Coma cluster, the Virgo cluster, Abell 2029, and Abell 1689. All of these clusters are completely covered by the SDSS so clusters only partly covered by the SDSS will no have as precise a measurement although I have taken steps to compensate for partly covered clusters.
After all the structures have been isolated, a check is made to see if any of them are pancakes. For a manual approach it is determined by an eyeball test if any structure actually are pancakes. In my program I use several tests to avoid false positives as checking them all by eye would take too long. After all pancakes has been found, they are cross checked between different thresholds. It is not expected that there is a specific pattern across the thresholds, but some pancakes will show up at several thresholds and some of these thresholds might reveal more well behaved and regular pancakes than the others.

e) Include data along the edges of the pancake. Due to how the galaxies in the pancakes are selected there is an inherent bias against galaxies at the edge of the pancakes. This is due to galaxies at the edge only having a dense amount of neighbours towards the pancakes while the density is expected to fall off heavily on the other side.
To counteract this bias, galaxies close to the edge of the pancake are included as part of the pancake. The distance from the edge of the pancake which these galaxies has to be is half the size of the distance I use for the friends of friends algorithm. This is done to make the pancakes more well behaved. It also diminishes the clumping at the edge of pancakes in cases where a single galaxy a bit outside the pancake is selected as part if it due to a small fluctuation in density around the galaxy.

f) Optimize number of slices. Once one or more pancakes have been identified the number of slices including when analysing the pancake is optimized. This is done to get the highest possible S/N ratio and will often remove unnecessary clumps in and around the pancake. This is done by looking at how much of the pancakes is contained in the different individual slices in the signal region and around it. Typically a single pancake is contained in 4 slices with a somewhat equal distribution among each slice which individually show signs of a diffuse pancake.

If some slices has to be added or removed to provide a more optimal pancake the whole process has to be repeated again as the background will change slightly and some pancakes might end up being more diffuse leading to other thresholds being better suited for that pancake. If the end result leads to a more messy pancake the new result is discarded and the old result is used instead.

2.2 Automatic pancake selection

There are a few differences between manually searching for pancakes and doing so automatically. The overall method is largely the same but I need to make a lot of tests to check for false positives that would otherwise be an easy eyeball test. In this section I will take take each step presented in the last section which requires some sort of change to work for an automatic program and explains what problems there are, and what I have done to solve them.

2.2.1 Selecing the pancakes from the remains

After finding all galaxies in the overdense regions of (R,v_{los}), it is relatively easy to find the structures using a friends of friends algorithm. This leads to a lot of different structures of which only a few a pancakes. Some of them are going to be galaxy groups or filaments but most of them are the result of random overdensities and have no real coherence or pattern. In some cases these random structures will end up looking somewhat like pancakes, and while a human would be easily able to tell the difference an automated program cannot.

To solve this I have several parameters which I use to test pancakes. For the rest of this section I will talk about these tests. None of the tuning of the tests is done by mathematical calculations only but always by a mix of empirical tests and mathematical formulas. For some of the tests purely mathematical limits could be found but it is outside the scope of this paper.

a) Cluster mass test. Most random structures will not make a very good fit on the Universal Infall Velocity profile and will often require the cluster to have masses much heavier or lighter than what can be reasonably assumed (see figure 14). As an example, structures which are horizontal in (R,v_{los}) will require a mass of $0M_{\odot}$. To quickly remove these structures I make a test with the requirement that the mass parameter of the fit has to be between $10^{13}M_{\odot}$ and $10^{17}M_{\odot}$. Since one of the benefits of the method is to find the mass of the cluster any pancakes are connected to it is in general bad conduct to create checks using the mass. In this case however the boundaries are so large that any realistic cluster cannot have masses outside the range at which pancakes are accepted, ensuring that this check only removes structures that are not pancakes.

I could have made a more strict test where I looked up mass estimates for individual clusters. However this would create results biased towards the masses I want to see, and there is some evidence that the shape of the cluster has a large effect on the estimated mass which might cause the estimate gained from the pancake to be either larger or smaller than the actual mass of the cluster.

b) Length against dispersion. This test measures the length of the pancake against its dispersion. To give an accurate calculation I use the tangential dispersion instead of the line of sight velocity dispersion. The reason for this is that pancakes with a large angle to its projected radius will display a higher dispersion than if it had a small angle. To do this I calculate the dispersion from the Universal Infall Velocity profile's fit of the pancake.

This test defines most of what a pancake is expected to look like and is also what removes most of the structures that are obviously not pancakes (see figure 15). The reason I can use this test for so much is that the pancakes I am looking for are cold, elongated structures which are weakly dominated by the Hubble flow and this method tests the structures for two of those three characteristics. Due to the requirement that there has to be a low dispersion around the Universal Infall Velocity profile's fit of the pancake the program will only find pancakes with a low uncertainty on the fit parameters. While it is not unthinkable that there could be pancakes which does

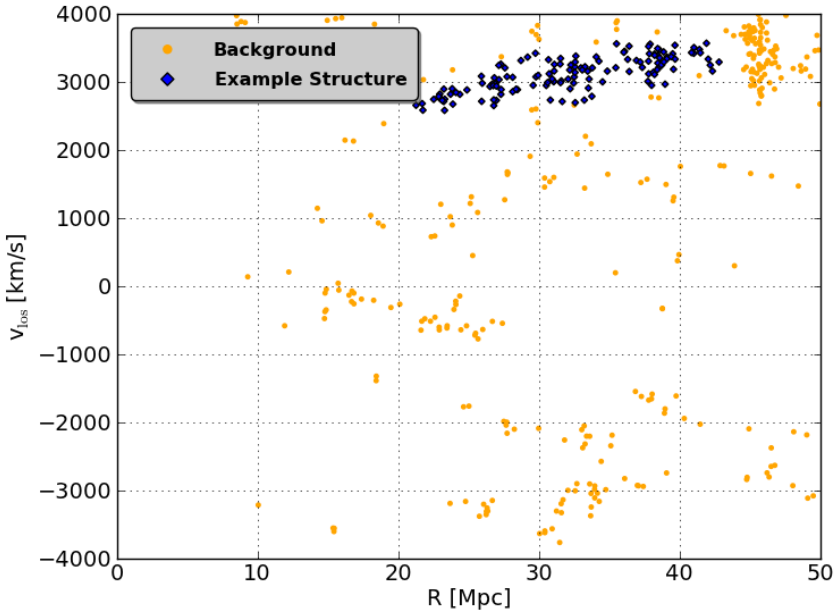

Figure 14: *If the Universal Infall Velocity profile is fitted to this structure it would cross $v = 0$ for to the left of $R = 0$ which results in a predicted cluster mass far lower than any cluster observed. This is obviously not the case, so it cannot be a pancake. The high, almost constant, velocity relative to the cluster suggests that it could be a filament but more tests would be required to confirm this.*

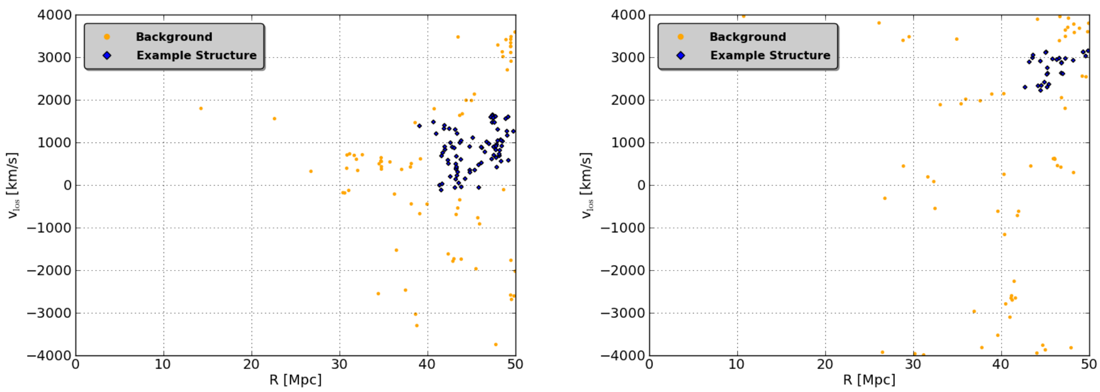

Figure 15: *Left: A Random structure that displays the characteristics of a pancake but is very dispersed to the degree of looking like something between a galaxy group and a random cluster. If these things are ignored it makes a fit with the Universal Infall Velocity profile that gives a mass inside the limits of what is expected. Right: A small structure that displays many of the qualities of a pancake but has a few galaxies at its upper left side. These pancakes does not increase its dispersion to the point where I would normally exclude it, but it does make the pancake too wide compared to its length. While there is a chance that this structure might actually be a pancake, the galaxies at its top, left side changes the UIV fit too much and since I have no way to remove those galaxies without creating a bias I have chosen to exclude this structure.*

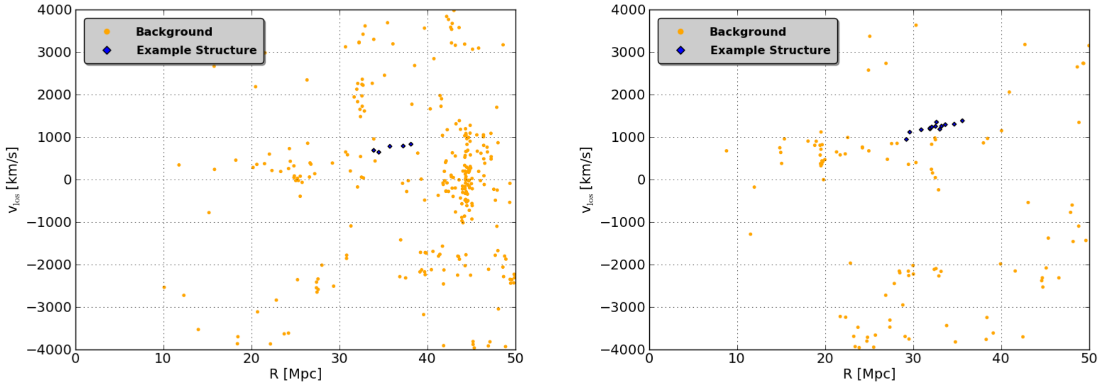

Figure 16: *Left: Typically case of a small string of galaxies forming an elongated structure with very low dispersion. While these might be pancakes there is a high chance they have just formed randomly and are therefore not included in my catalogue. Right: A larger case than the one presented left. Here there are 5-6 galaxies forming a straight line with many of the characteristics expected of a pancake. More galaxies get added on when the program includes galaxies at the edge of the structure as explained in 2.1.*

not display this characteristics, all of those will be highly irregular and by definition have huge uncertainty in the Universal Infall Velocity profile fit. The two pancakes which have currently been found was found manually without tests on of the dispersion. Both of them were however shown to be very cold [6].

c) Length against width test. Beside the dispersion I also do a test on the width of the pancake against the length. This is done to ensure that there are no massive outliers in either or both sides of a potential pancake (see figure 15). The limit for this test is very loose only requiring the length to be 50% longer than the width. By not tuning it to be very strict I allow for pancakes which have not yet become completely sheet like. While this test in general is not required there are a few edge cases which requires it. These typically include galaxy groups which are heavily biased towards the pancake but has a few remaining members far from it.

d) Size test. This is a simple test to eliminate cases where a few galaxies have formed a somewhat straight string or a small amount of galaxies have created a pancake like structure (see figure 16). The first case will sometimes happen randomly with 3-5 galaxies and while it may in fact be a pancake, it is not statistically significant, since if just one of the member galaxies are just randomly placed the way it is in (R,v_{los}), then the pancake's fit to the Universal Infall Velocity profile would change a lot by removing that galaxy. The second case with a small group of galaxies looking a lot like a pancake is very similar. This can arise from a combination of the case with 3-5 galaxy pancake and then having a lot of extra pancakes included after including pancakes in the edge. It will mostly happen in very rich cluster, or clusters many member galaxies have been discovered. To solve this I added a minimum required number of galaxies for any structure to be considered a pancake. The numbers I have found to work best are that the pancake has to have at least 20 member galaxies and at least contain 0.5% of the total number of galaxies in the cluster.

e) Zero v proximity test. The Universal Infall Velocity profile predicts an average infall of 0 at some points. This results in some pancakes crossing zero line of sight velocity (see figure 17). There are a couple of reason I do not want these pancakes. First off is that this method assumes that the whole pancake is drifting away from the cluster and in this scenario some of it is dominated by the gravitational pull of the cluster and therefore drifting towards it. Beside this the fit from the Universal Infall Velocity profile requires huge differences in parameters to display changes in this area and therefore the error bars on the fitting parameters become very large. Another problem related to pancakes close to zero v is if the pancake has almost no angle to its projected radius (see figure 17. In this case it is also difficult to measure fit the parameters of the Universal Infall Velocity profile correctly as described in section 1.2.

In both these cases pancakes where only a small part is close to or beyond $v = 0$ which are unusable. While pancakes which have small parts in this area are harder to make precise measurement with

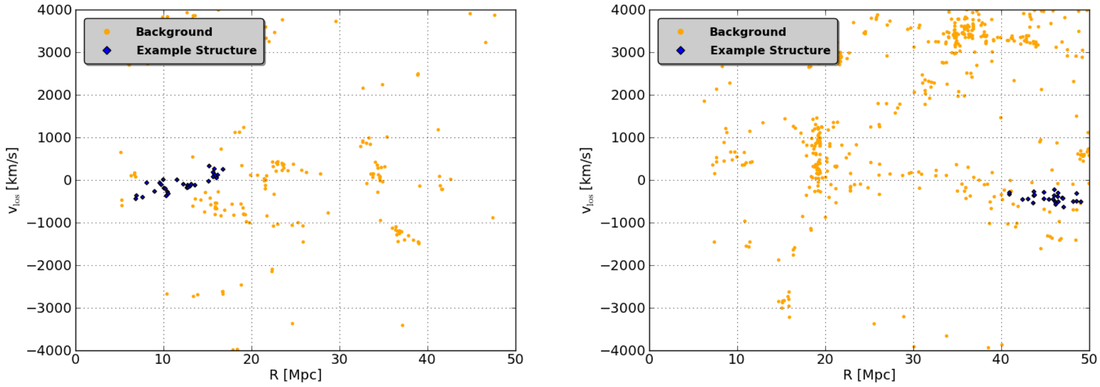

Figure 17: *Left: A pancake that crosses $v = 0$ and is therefore hard to apply the Universal Infall Velocity profile to. Besides this it is slightly clumped and it is therefore very likely that it is a random structure. Right: A pancake close to $v = 0$. This makes it hard to fit it to the Universal Infall Velocity profile but not as hard as for the pancake in the left figure. This structure however shows signs of clumping making it hard to get a good fit and therefore I have chosen to not include this structure as a pancake.*

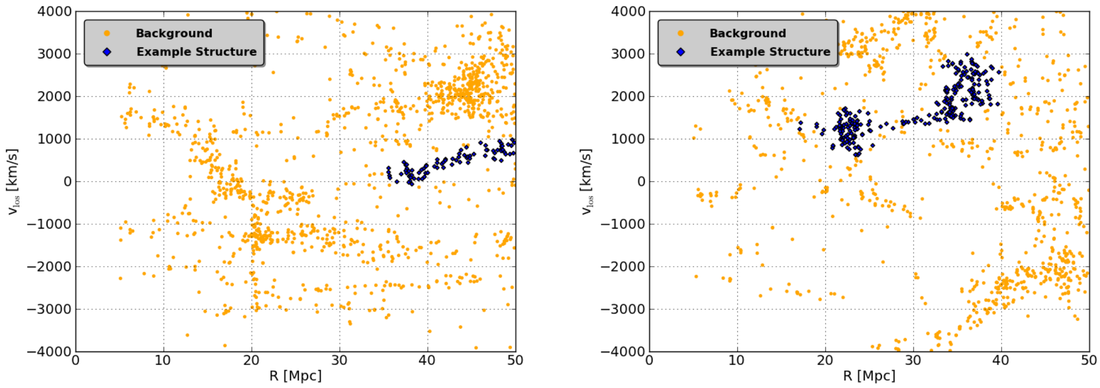

Figure 18: *Left: A typical pancake with a very even distribution of galaxies down its length. It is a bit worrying that it is so close to $v = 0$. Right: A very broken up structure with two very distinct groups in both ends. After having removed the groups a somewhat elongated, cold structure is left between them. This structure is however not a pancake as the Universal Infall Velocity profile predicts a negative cluster mass.*

they can still be used to a decent accuracy. To remove pancakes which are unusable I have discarded all pancakes with more than 70% of its member within $\pm 500 km/s$ and pancakes with more than 95% of its members within $\pm 1000 km/s$ unless the pancake is very well behaved. This is defined so that the length against dispersion and length against width tests becomes much stricter to offset the large uncertainty in the Universal Infall Velocity profile.

f) Clumped pancakes. Normally pancakes are expected to have their member galaxies somewhat evenly distributed along their length but sometimes there will be groups embedded in pancakes (see figure 18). This can be due to that part of the pancake having collapsed faster than the rest due to external gravitational fields, or a galaxy group can have been embedded in the pancake. In both cases the result is that a part of the pancake has a significantly larger dispersion and density of galaxies. In a few cases the group can be so dominant that the other tests removes the pancake altogether but in most cases the tests are tuned in such a way that the pancake is accepted. In these cases it can be hard to tell if there actually is a pancake with a group increasing its dispersion of a random structure with a group that by coincidence changes the Universal Infall Velocity profile fit in such a way that the whole structure is picked up as a pancake.

To test these structures I split the pancake into ten parts. I then calculate the percentage of the pancake in each part. I then test if 1,2 or 3 of these parts contain a much more significant part of the pancake that they should. If they do I test if the pancake is acceptable without the clumped parts. This removes all random structures where a group by coincidence makes it look like a pancake. It does however not remove cases where two groups which are close to each other in (R,v_{los}) have a small chain of galaxies between them. In these cases the small chain sometimes display characteristics of a pancake and while this might be the case, there is some evidence showing that it might indeed be a pancake. This has caused me to conclude that these cases should be included as pancakes.

The reason I can remove parts of the pancake like this and still be able to run tests on the rest is because no part of the pancake is unique and I thus expect every part of it to show characteristics of a pancake. The main problem is that the pancake becomes shorter if the group is located at either end of the pancake but in these cases it is already much harder to produce significant data from the pancake and requiring better data is therefore reasonable.

For small pancakes splitting them up in 10 parts can sometimes be a bit too much but since they are small I need a more accurate cut so that as much of the pancake as possible is kept. If the pancake is small I also do not expect to get any data from it if there are more than one group nested in it so 3 of the 10 parts should be sufficient to contain a single potential group. For large pancakes I can cut off some parts of it which is not contained in the group without loosing much statistical significance. The parts being larger also allows for several groups to be removed. Having 3 groups or more is however very unlikely so I doubt I would get any benefit for checking combinations of more than 3 parts.

I could have created a method to check if there is a change in density in the part of the group where a potential pancake would most like be, but hat is outside the scope of this paper.

2.3 Galaxy cluster mass estimation

After having located any pancakes in a cluster, I can use the the Universal Infall Velocity profile from equation (11) (see section 1.5.3) to get a fit of them. The fitting parameters here are the angle of the pancake to its projected radius and the mass of the galaxy cluster. To get good fit values for the virial mass, the angle α, and error bars I use a simple Markow Chain Monte Carlo (MCMC) code. The MCMC code is based on the papers [12, 13]. Since the fit only has two parameters I have not made a complicated MCMC code, and this together with making it more efficient could possibly be a topic for future work.

The Monte Carle method I use starts at a random point in the V_{vir}, α space and then take a step in a random direction, with a random step size which have been taken from a Gaussian distribution of possible step sizes in a suitable interval, where the interval is chosen in order to optimize the rate of convergence. This process is repeated until an area of maximum likelihood is found. To find this area the χ^2 value of the fit, using the new values, is compared to the χ^2 value of the fit using the previous values. If the new fit is better, a step is taken, otherwise there is a probability of $n < \exp(\chi^2_{old} - \chi^2_{new})$, that the step is taken, where n is a random number between 0 and 1. After this a new random step is attempted and this process continues until the number of steps taken equals a predefined value. For my program I use $5 * 10^5$ steps. I could have taken more

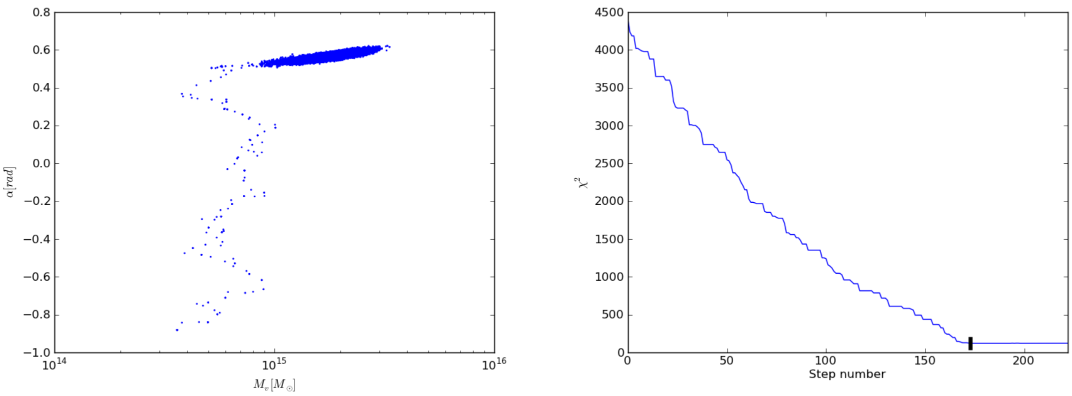

Figure 19: *Left: The parameter space of virial mass (M_v) vs the angle between the actual and projected radius (α), where the values obtained from one of our Markov Chain Monte Carlo (MCMC) runs are seen as blue circles. The burn in trail is clearly visible as a thin snaky line of data points. Right: Step number vs χ^2, zoomed in on the interval 0 to 500 steps, for one of our MCMC runs as the blue line, with the cut after the burn in phase indicated by a vertical black line.*

steps but I have found that with this number at least 10% of the steps will be after the MCMC code have found the area of maximal likelihood. While taking more steps could possibly give me better error bars, but the benefit would be quite small compared to the extra runtime it would require.

In order to reduce the noise made from starting at a random point in V_{vir}, α space, I remove the steps taken before reaching a decent fit. This is the so called "burn in phase" (see Figure 19). The removal is done so that the first time the code have a somewhat stable χ^2 value for 100 steps anything before those hundred steps i removed. This works because the steps taken before that period are very large and therefore often cause large shifts in the χ^2 value.

For each attempted step I either save the new parameter value, if the step is taken, or save the old value again, if the step is not taken.

This results in multiple entries with the same parameter value, if the step is not taken. By using the saved virial velocity values, an estimate of the virial mass can be made via:

$$M_v = \left(\frac{V_{vir}^3}{GH_0}\right)\sqrt{\frac{2}{D}}\frac{10^9 \cdot 3.08567758 \cdot 10^{19}}{1.9891 \cdot 10^{30}} M_\odot \quad (12)$$

Where $D = 100$ is a constant, 10^9 is from converting m^{-3} to km^{-3}, $3.08567758 \cdot 10^{19}$ is from converting Mpc to km and $(1.9891 \cdot 10^{30})^{-1}$ is from converting kg to solar mass, $M_\odot$.

After this I create lists of the different values for M_v and α I obtained by running the MCMC code. Using these lists I can then calculate the most probable values, as well as the standard deviation of those values.

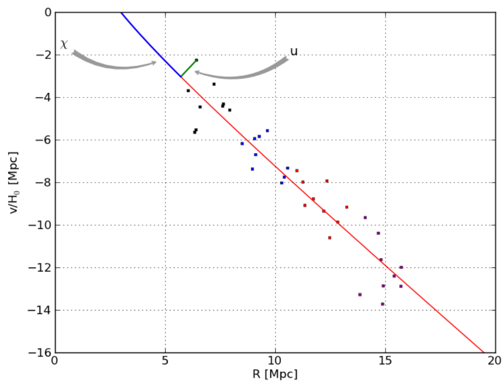

Figure 20: *A sample UIV fit through a pancake (red line) with χ (blue line) and u value (green line) indicated for one data point. Bins are given by different color markers.*

2.4 Pancake dispersion

As mentioned in section 2.2.1 I calculate the dispersion of the pancake in relation to the Universal Infall Velocity profile. Since I will be using this dispersion to get a measure of the how accurate

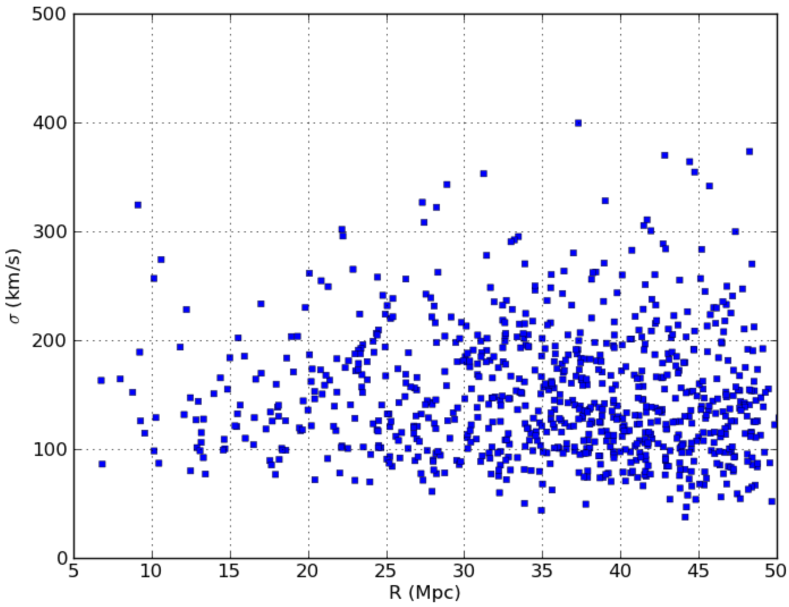

Figure 21: *This plot shows the velocity dispersion of each of the pancakes, or part of the pancake if it is long enough, against the projected radius of the center of that pancake. It can clearly be seen that by far most of then pancakes have a velocity dispersion of under 200 km/s. There are several points above this and even a few points above 300 km/s. These points are mostly far away from the galaxy cluster.*

my program is I will now explain exactly how it is done. I convert the v_{los} axis to units of Mpc by dividing with H_0, and by doing so I am able to create bins roughly perpendicular to the UIV fit (see Figure 20). By calculating the mean and standard deviation of the u values from each bin and then converting these values to km/s by multiplying with H_0, I get a measure of the dispersion in each bin of the pancake.

3 Results

Throughout this section I will show general statistics of what I have found together with examples of the pancakes I find. I do not show and talk about all the found pancakes since I have found a lot of them.

3.1 197 pancakes in 113 clusters

By applying my program on the SDSS and using the Abell catalogue to locate galaxy clusters I am able to locate 197 different pancakes. These pancakes are distributed between a total of 113 different clusters with 65 clusters containing 1 pancake, 26 clusters containing 2 pancakes, 14 clusters containing 3 pancakes, 3 clusters containing 4 pancakes, 4 clusters containing 5 pancakes, and 1 cluster containing 6 pancakes.
It should be noted that while I search through 684 cluster, most of them are not completely covered by the SDSS, which makes it harder to find pancakes. In most cases where the cluster is completely covered by the SDSS the program does manage to find at least one pancake. In cases where the cluster is close to us, such as the Coma cluster is, the program often finds multiple pancakes.

3.2 Pancake velocity dispersion

As stated in section 1.2.1 I expect the pancakes to be cold, coherent structures. To confirm that what I have found is indeed pancakes I plot their velocity dispersion against their projected radius.

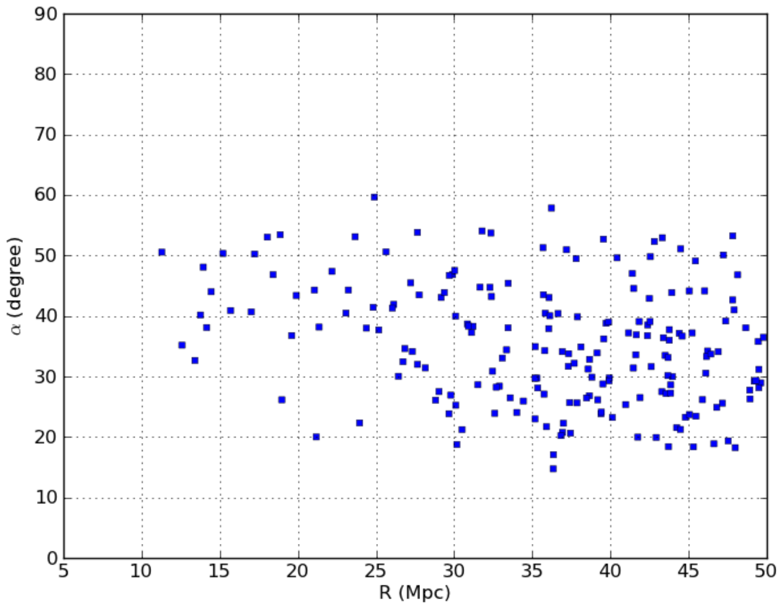

Figure 22: *Here I have plotted the angle between actual and projected radius against the projected radius for the pancakes I find. It is very clear that the most pancakes are in the 20 to 60 degree region with a few pancakes below 20 degrees. Pancakes at lower R also seem to mainly be in the region 30 to 50 degrees.*

For pancakes longer than 12 Mpc I split them in multiple parts to isolate groups inside the pancakes. This causes there to be a few outliers with velocity dispersions as high as I expect groups to have, but everything else should have low values if I indeed only find pancakes. As can be seen in figure 21 most of the pancakes are below 200 km/s which is the maximal velocity dispersion I expect of orderly pancakes. It should be noted that for pancakes longer than 12 Mpc I split them up in several parts depending on the length. This is done to isolate groups in pancakes where such groups will not dominate the whole pancake.
As can be seen in the figure most of the pancake parts above 200 km/s is located far away from the cluster. This is expected since there should be more random structures at those distances, and gravitational influence from other large structures might be larger than the cluster I am analysing when finding this pancake. Both of these factors result in larger velocity dispersions. The random structures might overlap with the pancakes and in cases where I select the part of the pancake where the random structure is dominant then it is only the few pancakes which belong to the pancake that bring down the velocity dispersion from the 300 to 400 km/s I expect from galaxy groups. On the other hand if pancakes are more influenced by other structures than by the cluster I analyse when finding the pancake then normally I should not find the pancake. However if it is only recently that the gravitational pull has become stronger from another structure then I expect to still be able to find them, albeit with larger velocity dispersions.

3.3 Pancake angle

In section 1.2 I state that the method is expected to work mainly in the ± 20 to 70 degrees region. While this seems to be true, based on figure 22 it should be possible to limit this region to ± 15 to 60 degrees. There also seems to be a weak coherence between the angles at which I find pancakes and the projected radius they are found at. For pancakes closer to the cluster than 25 Mpc I find very few pancakes outside of the ± 30 to 55 degrees region. This may be because I have found more pancakes beyond 25 Mpc compared to closer than 25 Mpc but it should be noted that I expect pancakes with a shallow angle to be harder to pick out from the $v = 0$ region if they are close to the cluster. This is because pancakes close to the cluster will also be closer to $v = 0$ giving a

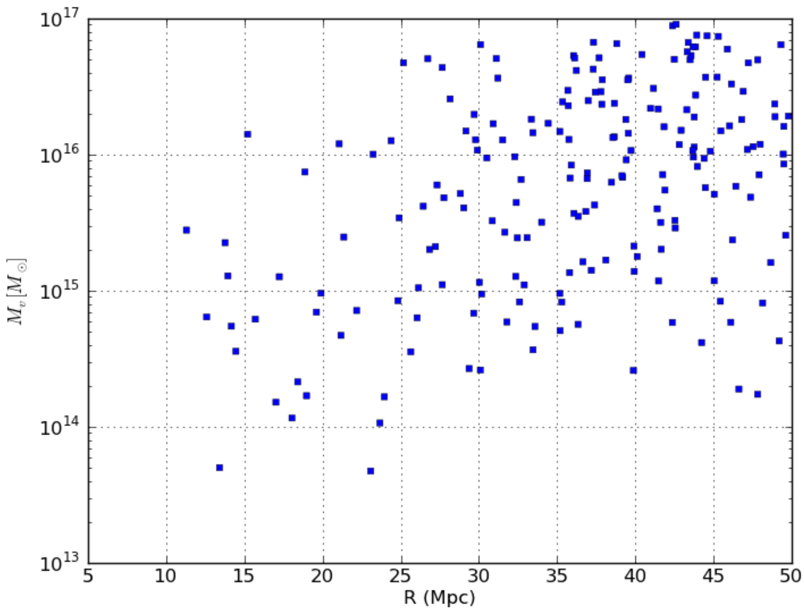

Figure 23: *As can be clearly seen the predicted masses for the clusters based on the pancakes are in many cases larger than the typical* 10^{14} *to a few* 10^{15}*. It should be noted that most pancakes which gives an estimate of very high masses are located very far away from the galaxy cluster. There also seem to be some correlation between* R *and* M_v*.*

possible explanation of why I find very few pancakes with a small angle close to the cluster.

3.4 Galaxy cluster mass

From the catalog of pancakes I have made, I use the Universal Infall Velocity profile to measure the mass of the galaxy clusters that contains the pancakes. Doing this I find some masses far larger than what I expect to find. There are a few things which could have caused this so I will go over the different problems that arrise when trying to use pancakes to calculate the mass of the galaxy cluster.

Clusters are not expected to be spherical and even in simple cases like an oblate spheroid cluster I expect to be able to see a difference between between measuring at the pole, that is the through the minor axis, and measuring through the equator. This difference should result in a larger measured mass at the equator than at the pole. This is due to the pancakes feeling a heavier pull from the cluster when positioned at the equator compared to the pole. I expect to find such pancakes further away from the galaxy cluster's centre since the Hubble flow only takes over farther away. Due to this effect I also expect that I can detect pancakes farther away if the it is located at the major axis than I would normally be able to. Figure 23 shows correlation like this suggesting that this is indeed the case.

3.5 Two clusters with multiple pancakes

To better give an example of why I think the measurements in very high masses are due to the shape of the galaxy cluster rather than what I find not being pancakes I will now present two different clusters. One of these clusters will show a stable mass measurement across the pancakes found in it while the other will show that the mass can fluctuate even for good pancakes in the same cluster.

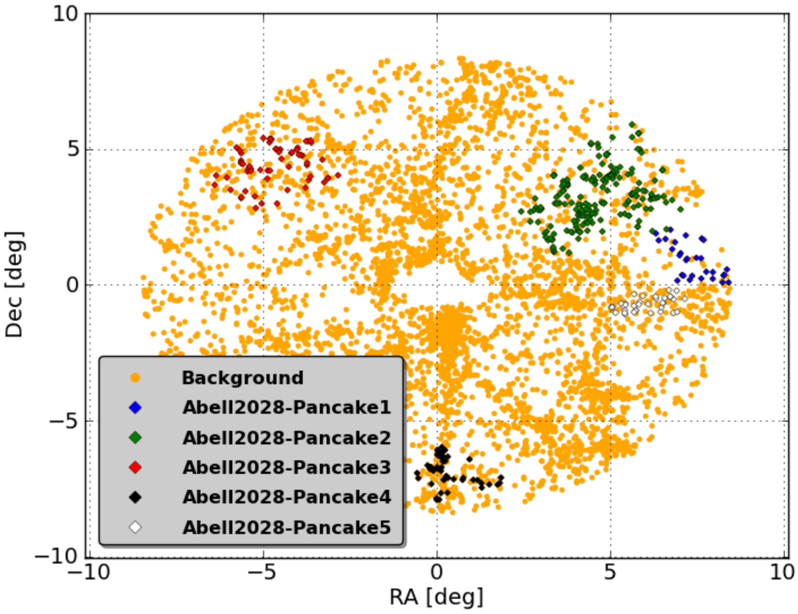

Figure 24: *The pancakes around Abell 2028 together with the background. Pancakes 1,2, and 5 are fairly close to each other, while pancake 3 and 4 are very isolated.*

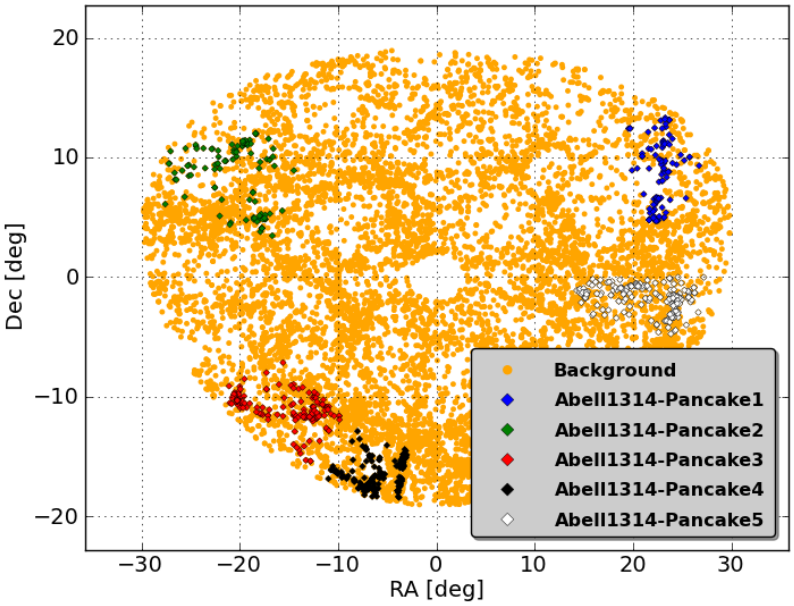

Figure 25: *The pancakes around Abell 1314 together with the background. Pancakes 1 and 5 and pancake 3 and 4 are respectively fairly close to each other, while pancake 2 is far from anything else. Note that the cluster is not spherical due to available data from SDSS.*

3.5.1 Abell 2028

I find five pancakes in Abell 2028 (see Figure 24) which measure the mass of the cluster to be $1.6^{+1.3}_{-1.3} \cdot 10^{16} M_\odot$, $9.5^{+1.9}_{-1.9} \cdot 10^{15} M_\odot$, $1.3^{+0.7}_{-0.7} \cdot 10^{16} M_\odot$, $1.1^{+0.9}_{-0.9} \cdot 10^{16} M_\odot$, and $1.7^{+1.0}_{-1.0} \cdot 10^{16} M_\odot$. Unfortunately the error bars a quite large, but it does give some insight into what range of masses the cluster can be expected to have. These measurements are all somewhat close, making a strong case for that I actually am measuring the mass of the cluster with no local interferences for the different pancakes that would change the measurement drastically.

3.5.2 Abell 1314

My program finds 5 pancakes in Abell 1314 (see Figure 25) which measure the mass of the cluster to be $7.0^{+6.2}_{-5.9} \cdot 10^{15} M_{\odot}$, $7.4^{+3.7}_{-3.9} \cdot 10^{15} M_{\odot}$, $8.1^{+8.6}_{-7.7} \cdot 10^{14} M_{\odot}$, $5.0^{+1.2}_{-1.0} \cdot 10^{16} M_{\odot}$, and $1.4^{+0.7}_{-0.8} \cdot 10^{15} M_{\odot}$. Here pancake 1 and 2 give measurements close to each other despite being on opposite sides of the cluster meaning there is a good chance this is somewhat close to the actual mass of the cluster unless the shape of the cluster increases both those mass measurements by an equal amount. Pancake 5 is fairly close to pancake 1 but there is a decrease in the measurement most likely caused by the shape of the cluster. Pancake 3 and 4 both give very different mass measurements, both from each other and from the other pancakes detected in the cluster. Despite being close together on the sky their angle towards their projected radius is estimated to be -47 degrees for pancake 3 and 53 degrees for pancake 4 meaning they are very far away from each other. Future research could possibly take clusters like these, where multiple pancakes are found, and give a rough map of the morphology the cluster would require for the pancakes to result in mass measurements such as these.

4 Final Remarks

After running my program through 683 different clusters I manage to find 197 pancakes in 113 different clusters. The rate of pancake finding is low mostly due to many of the clusters I search not being completely covered by the SDSS. I perform statistical checks on the whole catalogue to check if what I find actually is pancakes, and conclude that they are in fact pancakes although there are some large groups nested in some of the pancakes.

One of the goals of this research has from the start been to publish the found results as a paper as the first Zeldovich pancake catalogue. I further plan to publish the program I have used to create the catalogue after I have used the catalogue and the program to make tests and analyses on the catalogue.

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5 Appendix A

This list contains all the pancakes, their masses and their angle relative to their projected radius. I have severely rounded the numbers to three significant digits as the there often is a large uncertainty on the mass and angle estimates.

Cluster,Pancake number	Mass in $10^{11} M_{\odot}$	Angle in radians
Abell 23, Pancake 1	59900.0	-0.596
Abell 76, Pancake 1	534000.0	-0.662
Abell 102, Pancake 1	101000.0	0.773
Abell 117, Pancake 1	6840.0	-0.416
Abell 151, Pancake 1	51800.0	-0.455
Abell 225, Pancake 1	81900.0	0.523
Abell 240, Pancake 1	93900.0	-0.648
Abell 246, Pancake 1	114000.0	-0.628
Abell 261, Pancake 1	101000.0	0.625
Abell 261, Pancake 2	238000.0	0.573
Abell 279, Pancake 1	23600.0	-0.597
Abell 279, Pancake 2	3590.0	-0.768
Abell 400, Pancake 1	20100.0	-0.604
Abell 569, Pancake 1	17900.0	-0.405
Abell 634, Pancake 1	5870.0	0.533
Abell 634, Pancake 2	5660.0	-0.257
Abell 634, Pancake 3	644000.0	-0.441
Abell 671, Pancake 1	148000.0	-0.401
Abell 688, Pancake 1	756000.0	0.766
Abell 690, Pancake 1	2620.0	0.698
Abell 690, Pancake 2	41800.0	-0.524
Abell 690, Pancake 3	235000.0	-0.448
Abell 695, Pancake 1	126000.0	0.674
Abell 744, Pancake 1	141000.0	-0.879
Abell 744, Pancake 2	25600.0	-0.505
Abell 744, Pancake 3	48700.0	-0.684
Abell 757, Pancake 1	83800.0	0.379
Abell 757, Pancake 2	11000.0	0.496
Abell 779, Pancake 1	21100.0	0.794
Abell 779, Pancake 2	145000.0	0.664
Abell 779, Pancake 3	1070.0	0.927
Abell 779, Pancake 4	331000.0	-0.581
Abell 779, Pancake 5	71200.0	0.716
Abell 858, Pancake 1	7160.0	-0.827
Abell 858, Pancake 2	654000.0	-0.522
Abell 858, Pancake 3	6960.0	0.642
Abell 957, Pancake 1	5490.0	0.665
Abell 1003, Pancake 1	58600.0	-0.588
Abell 1016, Pancake 1	27900.0	0.882
Abell 1020, Pancake 1	108000.0	0.818
Abell 1060, Pancake 1	499000.0	0.584
Abell 1100, Pancake 1	217000.0	0.548
Abell 1100, Pancake 2	5900.0	0.943
Abell 1100, Pancake 3	12900.0	-0.839
Abell 1139, Pancake 1	181000.0	-0.434
Abell 1139, Pancake 2	189000.0	-0.659
Abell 1139, Pancake 3	290000.0	0.864
Abell 1139, Pancake 4	1690.0	0.456

Cluster,Pancake number	Mass in $10^{11} M_{\odot}$	Angle in radians
Abell 1142, Pancake 1	14100.0	0.889
Abell 1142, Pancake 2	1730.0	0.745
Abell 1142, Pancake 3	10500.0	-0.732
Abell 1142, Pancake 4	42700.0	-0.448
Abell 1142, Pancake 5	502000.0	0.749
Abell 1149, Pancake 1	3560.0	0.883
Abell 1149, Pancake 2	31900.0	-0.420
Abell 1169, Pancake 1	143000.0	0.920
Abell 1185, Pancake 1	44500.0	0.754
Abell 1185, Pancake 2	115000.0	-0.338
Abell 1187, Pancake 1	20200.0	0.644
Abell 1213, Pancake 1	109000.0	-0.447
Abell 1213, Pancake 2	2600.0	0.680
Abell 1213, Pancake 3	66700.0	0.595
Abell 1216, Pancake 1	74600.0	-0.933
Abell 1216, Pancake 2	40000.0	0.821
Abell 1216, Pancake 3	119000.0	0.318
Abell 1218, Pancake 1	32700.0	-0.675
Abell 1228, Pancake 1	214000.0	0.480
Abell 1238, Pancake 1	68100.0	0.456
Abell 1238, Pancake 2	6330.0	0.721
Abell 1257, Pancake 1	5470.0	0.462
Abell 1257, Pancake 2	8280.0	0.417
Abell 1257, Pancake 3	1160.0	-0.926
Abell 1267, Pancake 1	507000.0	0.566
Abell 1267, Pancake 2	4280.0	0.510
Abell 1267, Pancake 3	37000.0	0.751
Abell 1270, Pancake 1	16800.0	-0.609
Abell 1270, Pancake 2	515000.0	-0.562
Abell 1275, Pancake 1	365000.0	-0.668
Abell 1291, Pancake 1	474000.0	0.658
Abell 1308, Pancake 1	596000.0	0.457
Abell 1314, Pancake 1	70000.0	-0.592
Abell 1314, Pancake 2	73500.0	-0.362
Abell 1314, Pancake 3	8130.0	-0.817
Abell 1314, Pancake 4	497000.0	0.929
Abell 1314, Pancake 5	13900.0	-0.520
Abell 1322, Pancake 1	365000.0	0.632
Abell 1337, Pancake 1	12700.0	0.877
Abell 1354, Pancake 1	545000.0	-0.866
Abell 1356, Pancake 1	24500.0	0.539
Abell 1365, Pancake 1	747000.0	0.640
Abell 1367, Pancake 1	249000.0	0.389
Abell 1367, Pancake 2	48300.0	0.759
Abell 1372, Pancake 1	219000.0	0.443
Abell 1373, Pancake 1	535000.0	0.474
Abell 1377, Pancake 1	11800.0	0.770
Abell 1377, Pancake 2	96600.0	-0.781
Abell 1377, Pancake 3	181000.0	0.416
Abell 1383, Pancake 1	474.0	0.706
Abell 1385, Pancake 1	127000.0	-0.663
Abell 1468, Pancake 1	28900.0	0.869
Abell 1496, Pancake 1	11100.0	0.559
Abell 1507, Pancake 1	416000.0	1.010
Abell 1507, Pancake 2	371000.0	0.649
Abell 1541, Pancake 1	198000.0	-0.815

Cluster,Pancake number	Mass in $10^{11} M_{\odot}$	Angle in radians
Abell 1552, Pancake 1	885000.0	-0.672
Abell 1552, Pancake 2	96000.0	-0.321
Abell 1559, Pancake 1	163000.0	-0.771
Abell 1569, Pancake 1	71300.0	0.349
Abell 1589, Pancake 1	501.0	0.570
Abell 1650, Pancake 1	22500.0	-0.701
Abell 1650, Pancake 2	6180.0	0.714
Abell 1656, Pancake 1	13600.0	0.598
Abell 1656, Pancake 2	288000.0	-0.360
Abell 1749, Pancake 1	120000.0	0.773
Abell 1749, Pancake 2	1900.0	0.329
Abell 1750, Pancake 1	1660.0	0.390
Abell 1767, Pancake 1	9470.0	-0.327
Abell 1767, Pancake 2	642000.0	-0.512
Abell 1767, Pancake 3	437000.0	-0.939
Abell 1775, Pancake 1	160000.0	0.682
Abell 1781, Pancake 1	38200.0	-0.353
Abell 1800, Pancake 1	119000.0	0.913
Abell 1800, Pancake 2	31800.0	0.586
Abell 1809, Pancake 1	54900.0	0.463
Abell 1809, Pancake 2	135000.0	0.468
Abell 1827, Pancake 1	26900.0	0.781
Abell 1831, Pancake 1	24800.0	0.666
Abell 1873, Pancake 1	129000.0	0.473
Abell 1877, Pancake 1	355000.0	0.696
Abell 1890, Pancake 1	65700.0	0.493
Abell 1890, Pancake 2	297000.0	0.895
Abell 1899, Pancake 1	34300.0	1.040
Abell 1904, Pancake 1	667000.0	-0.635
Abell 1913, Pancake 1	150000.0	-0.409
Abell 1913, Pancake 2	6420.0	0.614
Abell 1913, Pancake 3	12700.0	0.938
Abell 1913, Pancake 4	8260.0	0.519
Abell 1913, Pancake 5	182000.0	0.601
Abell 1913, Pancake 6	16300.0	-0.705
Abell 1930, Pancake 1	21300.0	-0.511
Abell 1976, Pancake 1	307000.0	0.649
Abell 1983, Pancake 1	8450.0	-0.723
Abell 1983, Pancake 2	16100.0	-0.664
Abell 1983, Pancake 3	472000.0	0.874
Abell 1986, Pancake 1	619000.0	0.475
Abell 1988, Pancake 1	4700.0	0.349
Abell 1988, Pancake 2	292000.0	0.595
Abell 1991, Pancake 1	11500.0	0.830
Abell 2004, Pancake 1	149000.0	0.752
Abell 2022, Pancake 1	8370.0	0.857
Abell 2022, Pancake 2	67300.0	-0.706
Abell 2028, Pancake 1	132000.0	-0.471
Abell 2028, Pancake 2	94300.0	-0.370
Abell 2028, Pancake 3	113000.0	0.458
Abell 2028, Pancake 4	137000.0	-0.549
Abell 2028, Pancake 5	145000.0	-0.432

Cluster,Pancake number	Mass in $10^{11} M_{\odot}$	Angle in radians
Abell 2029, Pancake 1	509000.0	-0.651
Abell 2029, Pancake 2	3690.0	0.793
Abell 2029, Pancake 3	669000.0	0.589
Abell 2029, Pancake 4	24500.0	-0.577
Abell 2040, Pancake 1	621000.0	0.578
Abell 2040, Pancake 2	11800.0	0.778
Abell 2052, Pancake 1	62700.0	-0.462
Abell 2052, Pancake 2	1520.0	-0.710
Abell 2052, Pancake 3	4160.0	0.376
Abell 2055, Pancake 1	274000.0	0.500
Abell 2063, Pancake 1	91700.0	-0.421
Abell 2063, Pancake 2	32900.0	-0.682
Abell 2067, Pancake 1	257000.0	-0.548
Abell 2107, Pancake 1	570000.0	0.924
Abell 2107, Pancake 2	371000.0	0.892
Abell 2108, Pancake 1	192000.0	-0.637
Abell 2108, Pancake 2	9590.0	0.757
Abell 2108, Pancake 3	907000.0	0.552
Abell 2108, Pancake 4	190000.0	-0.459
Abell 2124, Pancake 1	9560.0	-0.518
Abell 2142, Pancake 1	35200.0	-0.298
Abell 2147, Pancake 1	425000.0	-0.553
Abell 2148, Pancake 1	2140.0	0.817
Abell 2148, Pancake 2	244000.0	0.490
Abell 2148, Pancake 3	2680.0	-0.766
Abell 2151, Pancake 1	40700.0	-0.480
Abell 2151, Pancake 2	57200.0	-0.371
Abell 2152, Pancake 1	134000.0	-0.545
Abell 2152, Pancake 2	5850.0	0.641
Abell 2162, Pancake 1	128000.0	-0.500
Abell 2162, Pancake 2	513000.0	0.699
Abell 2178, Pancake 1	236000.0	0.484
Abell 2178, Pancake 2	106000.0	0.406
Abell 2184, Pancake 1	5090.0	0.610
Abell 2197, Pancake 1	354000.0	0.502
Abell 2257, Pancake 1	229000.0	0.759
Abell 2366, Pancake 1	151000.0	0.348
Abell 2440, Pancake 1	85400.0	-0.544
Abell 2440, Pancake 2	169000.0	-0.669
Abell 2448, Pancake 1	51200.0	0.414
Abell 2462, Pancake 1	526000.0	0.269

6 Appendix B

Because of the the possibility of calculating on the morphology and the increased number of estimates on the mass, clusters with a sizeable number of pancakes are the most interesting. For that reason I will here show the clusters where I have found many pancakes. Note that since some of these clusters are very dense, some of the pancakes will have groups nested in them. These pancakes might not look like pancakes on a first look but once the part where the group is nested a pancake structure will emerge.

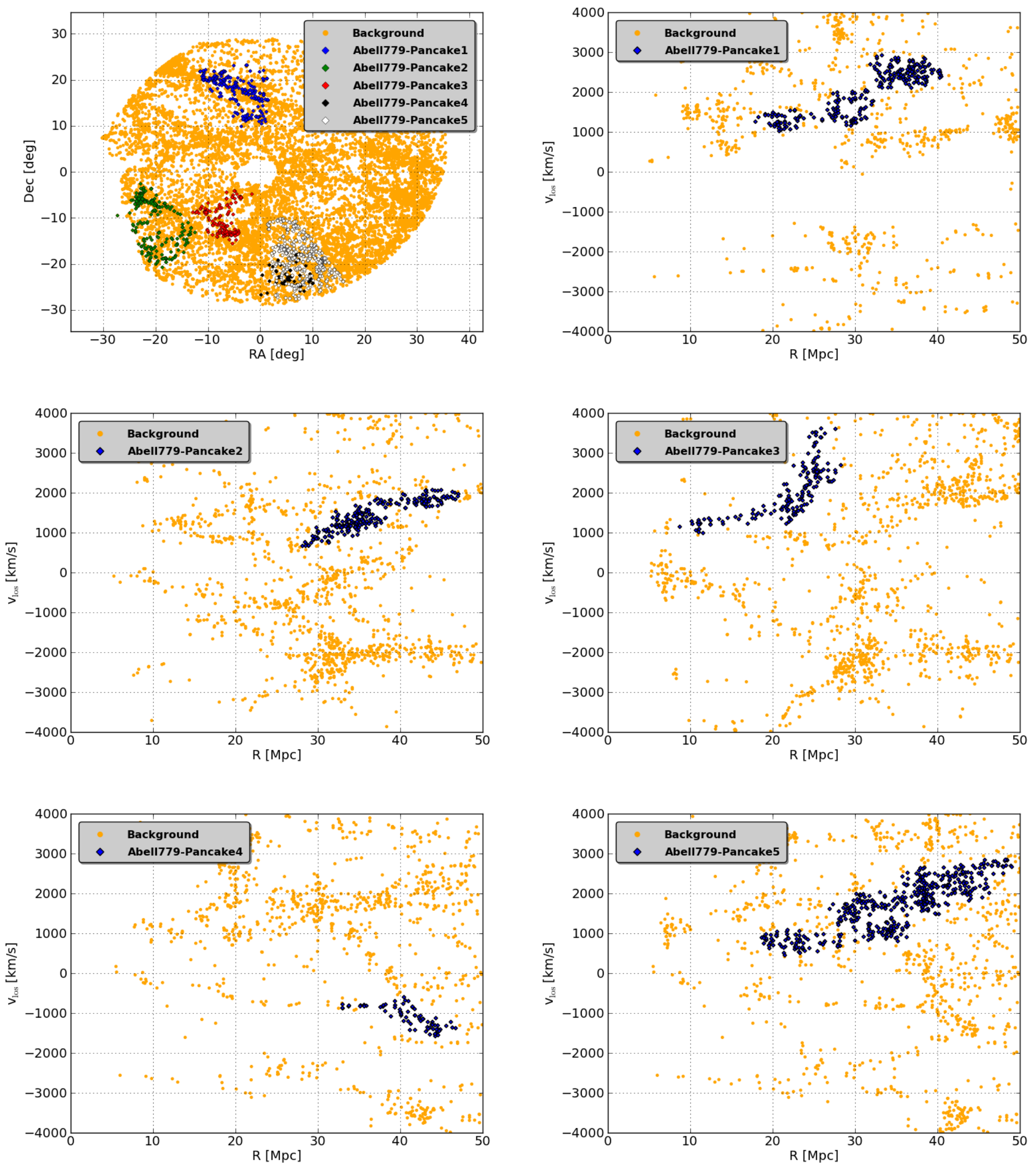

Figure 26: *Pancakes from analyzing Abell 779.*

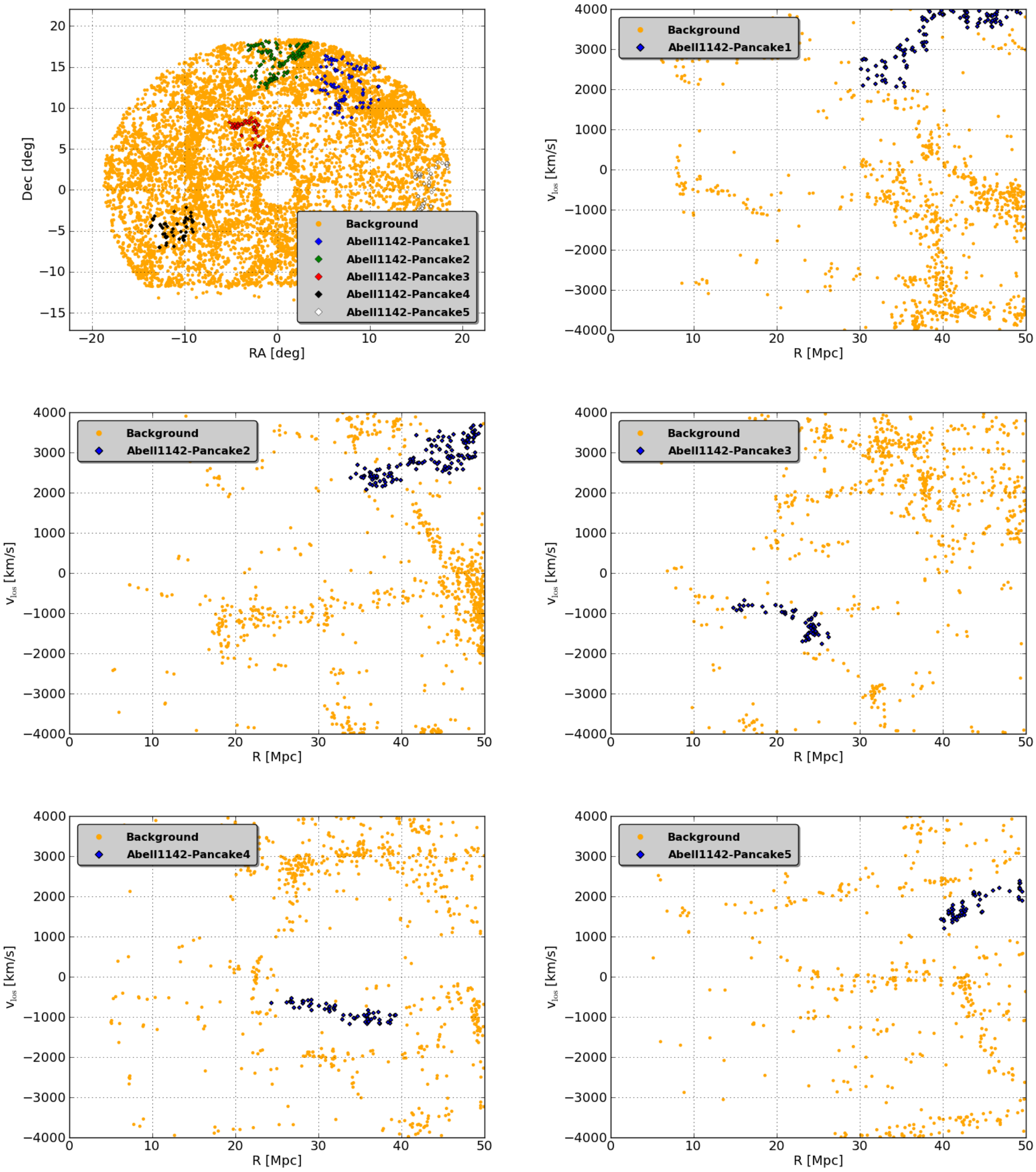

Figure 27: *Pancakes from analyzing Abell 1142.*

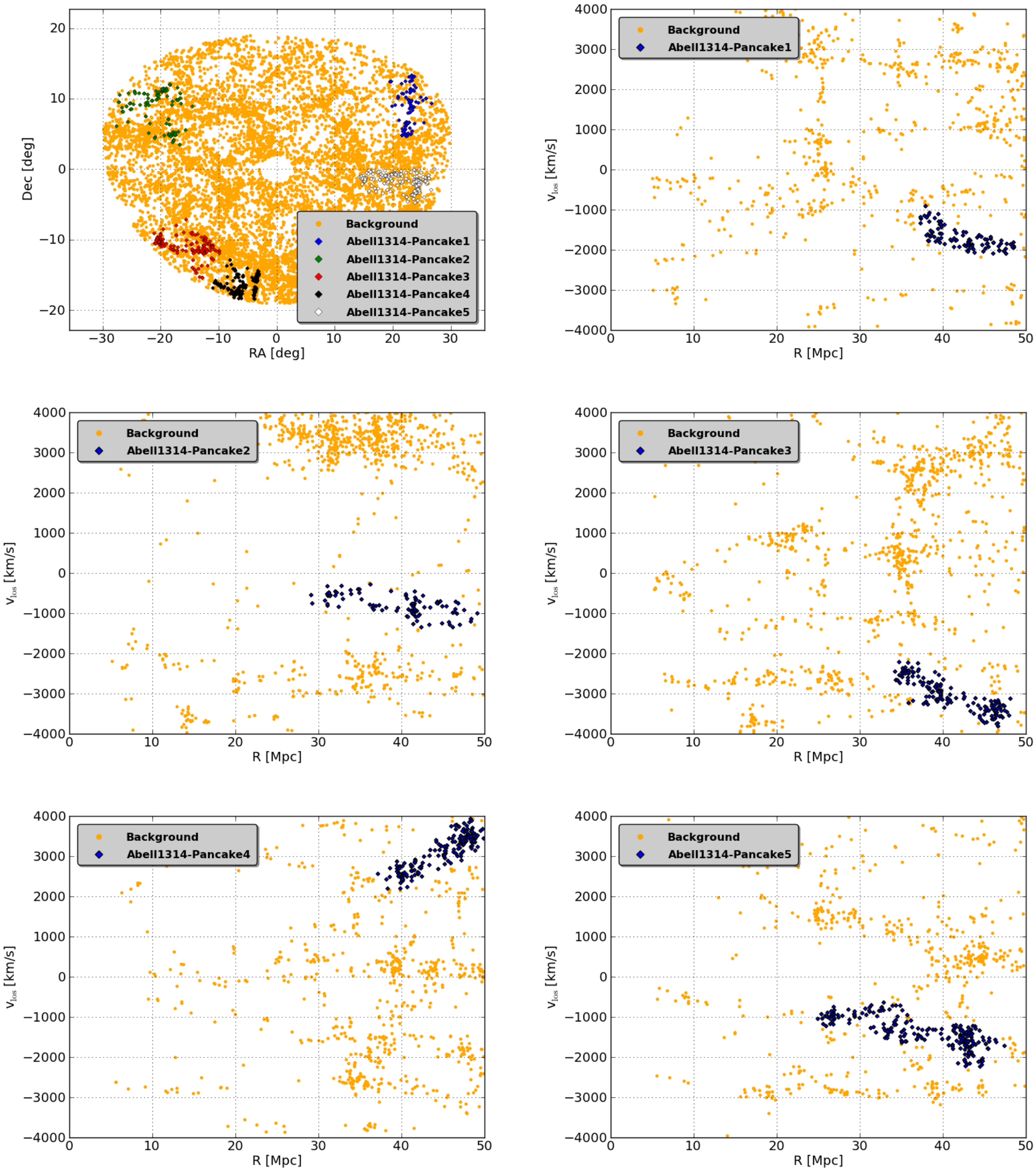

Figure 28: *Pancakes from analyzing Abell 1314.*

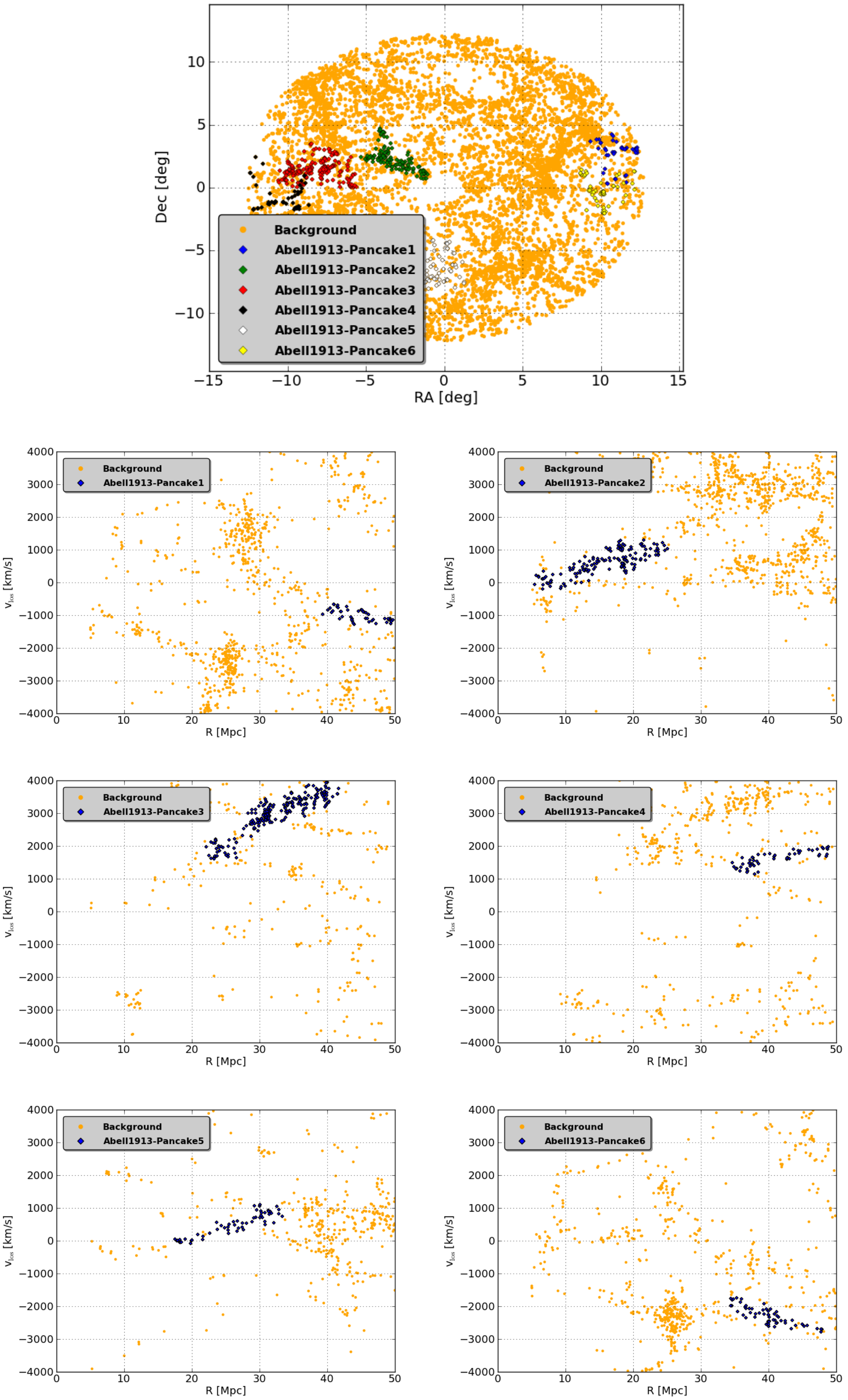

Figure 29: *Pancakes from analyzing Abell 1913.*

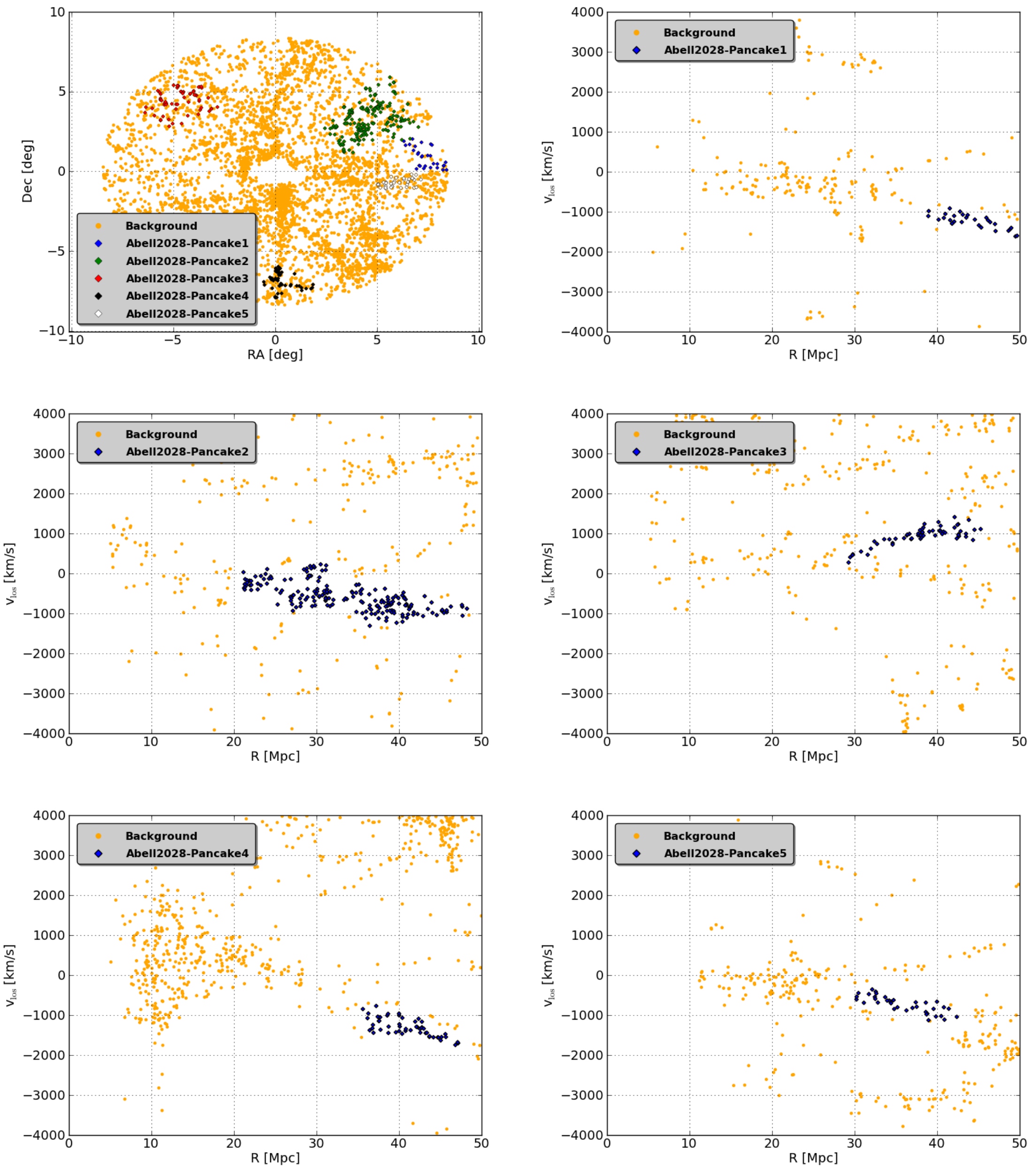

Figure 30: *Pancakes from analyzing Abell 2028.*