Validating and Cleaning Data

This exercise focusses on using tools to validate, clean explore data sets.

Introduction

A big problem with publicly available datasets is the number of errors within them. These problems vary from simple spelling errors, to the more complex problems involving misuse of units. This exercise is going to evaluate the following problems and related solutions:

1. **Date Validation**
   One of the most common problems in data is mixed date formats, this can be particularly troublesome when you have British and American date formats e.g. (7/12/2012 and 12/31/2012).

2. **Multiple Representations**
   Most common in datasets containing abbreviations, for example in location data or role based data. It is common that abbreviations will change and even be present in fully expanded form (e.g Vice-President Marketing and VP Marketing)

3. **Summation Records**
   When data has been extracted from a spreadsheet application, it is common to be left with both columns and rows of data containing the sums (or other formula) of the other data. While not an error, it is inconvenient when you want to re-process the data.

4. **Duplicate Record Detection**
   Duplicated records are common place both at the point of entry (by a human) but also a common occurrence when exporting a huge amount of data from multiple systems. It is often the case that the data has been duplicated in order to speed up searching across multiple domains where the data is applicable in both.

5. **Mixed use of numerical scales**
   A common, but critical, failure in data that can lead to audit failure. Outliers are often clear to see as one record may contain a figure multiple factors bigger than any other.

6. **Redundant Data**
   Redundant data is not required, thus it is common that errors are made when entering it.

7. **Numeric Ranges**
   Numeric ranges, often used to anonymise data, cause problems when wanting to explore and visualise the data.

8. **Spelling Errors**
   Last but not least, while not critical in all cases, spelling errors can lead to awkwardness when querying and visualising data.

Importing Data

In order to carry out this exercise three datasets are required. Although the datasets are genuine, they have all been modified for this exercise. The modified datasets are available from the course website.

Dataset 1 – Louisiana Secretary of State Officials

This dataset lists the statewide and multi-parish elected officials, all elected officials in a parish, and all elected officials in an office e.g. all sheriffs in the state of Louisiana.

The original dataset is available at: http://www.sos.la.gov/tabid/136/Default.aspx (removed as of 1/7/2013)

Dataset 2 – Projects Dataset

This dataset lists project data available from the US Governments IT Dashboard system at http://www.itdashboard.gov/data_feeds. It covers the projected and actual costs and timings of a number of government funded projects in the US.

Dataset 3 – UK GP Earnings

This dataset lists earnings data for medical doctors in the UK from 2009. The original dataset is available from http://data.gov.uk/dataset/gp-earnings-and-expenses-2009-10

Importing into Google/Open Refine

In order to process the data requires the Google Refine (soon to be Open Refine) tool available from openrefine.org.

Refine is an application that runs on your local machine, meaning that you don't have to upload a large dataset to a web service. Additionally this has the benefit that the data remains private.

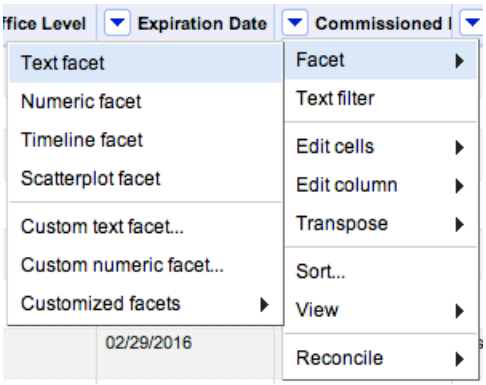
Once installed and running it should open a browser window on the refine home screen.

From the home screen, create a new project (per dataset) and run through the import options. In the majority of cases the default selections are correct.

1. Date Validation (Dataset 1)

One of the most common problems in datasets is that of mixed date formats. Sometimes the mix is simple to spot, e.g. 8-Sep-2013 vs 8/9/2013, sometimes not, e.g. 8/9/2013 vs 9/8/2013.

Due to this problem, the majority to tools, including refine, will simply import the data as a string object and not worry about the format or content of the object. In the case of refine a string object is known as a text object and can be browsed using a **text facet**.



In the dataset we are looking at in this exercise we are going to look at the range of dates in the **commissioned date** column.

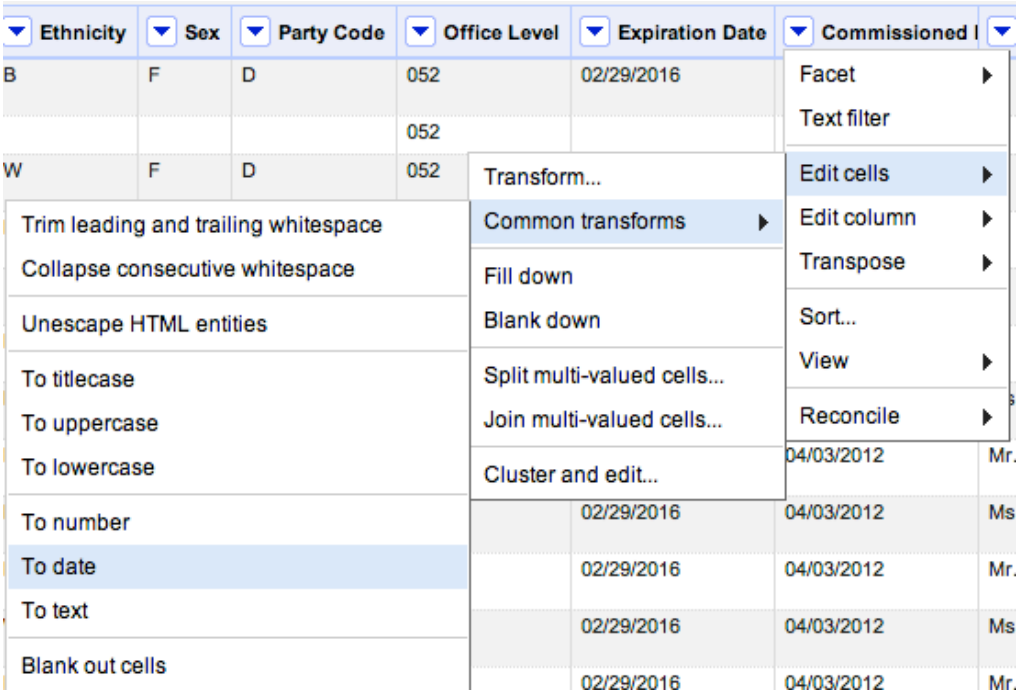
To apply a text facet, click the **downward arrow** next to the column title and select **text facet**.

Doing this will bring up a facet browser that you can use to view all the data in this column groups together. A quick scroll through this panel will reveal that we are in an American date format, with month first. There is one invalid date affecting 17 records.

To change this value, we could hover over the value and click the edit link, however we are going to look at a different method using a cell transform.

A cell transform allows us to change the type of the object. In this case from text to a date object.

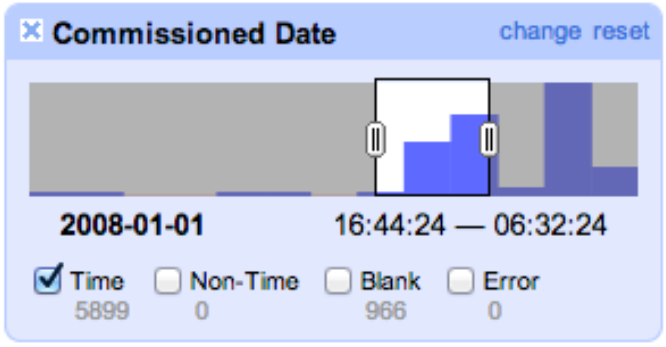
To do this select the **to date** option from the **column transforms** menu as shown.



Once done you will see that the **text facet** we applied previously is now full of random values that make no sense. This is because we cannot apply a text facet to an object that is not actually text anyone. At this point remove the text fact by clicking the close button in the top left corner of the facet browser.

In translating our text to a date object, refine has parsed over all the values in the date column and attempted to match the most common date format and used this as the basis to correct errors. In this case it would have recognised that the UK date format was being used and automatically corrected our 17 records from before. As this is such a common error, libraries for recognizing date formats are commonplace and used a lot on the web as well as other platforms.

In order to explore our new date objects we can apply a **timeline facet**. To do this click the downward arrow next to the column title and select **timeline facet** from the facet sub menu. The facet that appears will now display the range of dates and the number of items as a graph.



You probably want to untick the blank box while browsing the data in this way so that the facet is only displaying records that have a date associated with them. Note that if any of the rows had failed in the date translation they would appear as errors in this facet and would required manual investigation to clean.

2. Multiple Representations (Dataset 1)

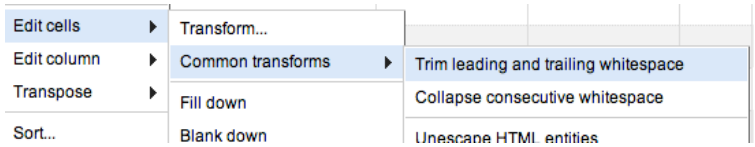
Due to the unique ways that people like to save time in data entry by abbreviating everything, it is very common to end up with several different representations of the same thing.

Thankfully the advanced clustering features of **Refine** can help us out.

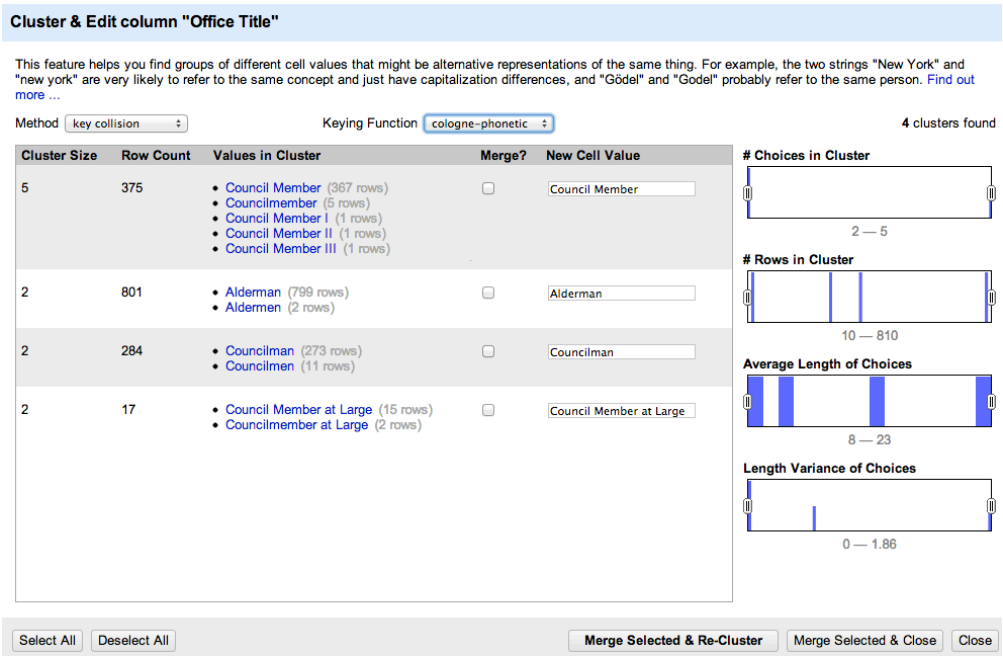
In this example we are going to use our Louisiana dataset and apply a **text facet** to the *Office Title* column. In doing this we can immediately see many errors in the data.

The errors highlighted all seem to involve trailing spaces and we can correct this in two ways. Firstly we can directly edit each value by hand, by hovering over it and clicking the **edit** button. Try this with the **Assessor** values, upon saving your edit you should see them group together showing 64 records.

Perhaps a more useful way however is to use a **trim spaces transform** on the *Office Title* column to clean them all in one go.



While this has eliminated many of the errors, others still remain, such as “Council Member” and “CouncilMember”. To fix these errors we can use the clustering techniques available in Refine. To access these press the **cluster** button from the facet browser.

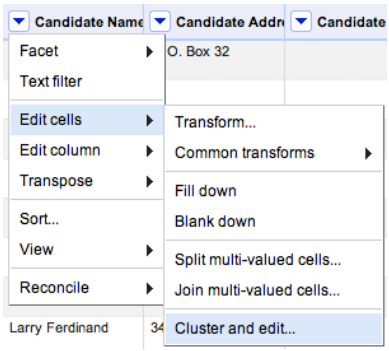


At the top of the clustering screen you can pick from many scientific methods and keying functions which all cluster data in slightly different ways. The method that will work best will very much depend upon your dataset and thus it is worth browser through each method and function to find which one best suits your needs.

It may be necessary to use a combination of methods and functions, each time selecting a number of records you want to **merge**, entering the **new value** and then pressing **merge selected and re-cluster**.

3. Duplicate Record Detection (Dataset 1)

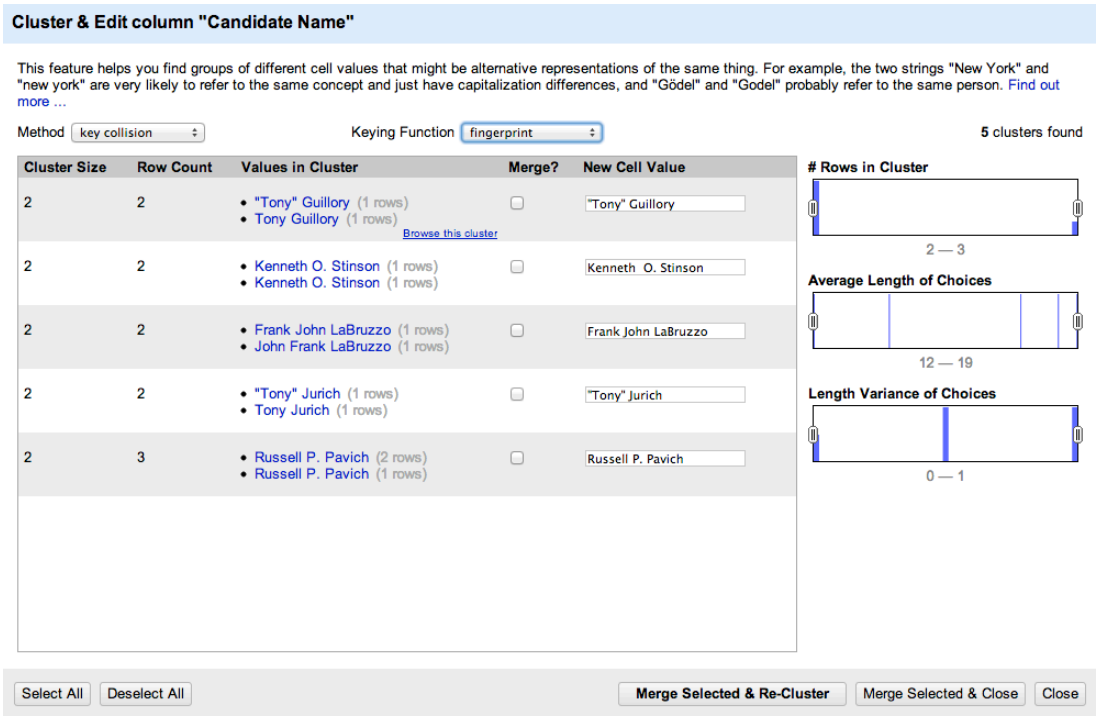
In order to identify duplicate rows we are going to look at the data in the *Candidate Name* column. Once again we are going to use the **clustering** function, but this time we need to examine the data more closely.



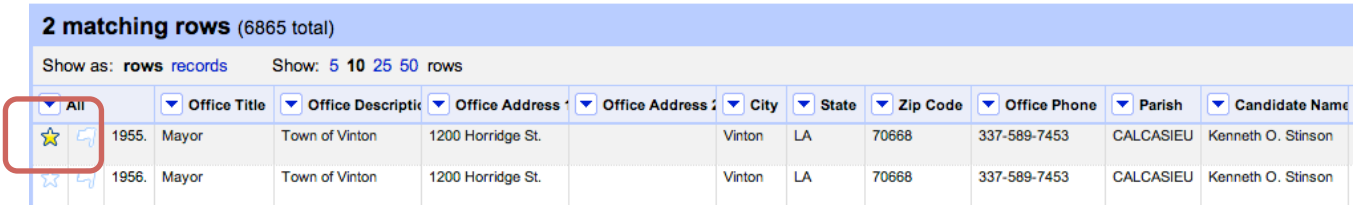
To bring up the clustering panel, select **cluster and edit** from the **edit cells** menu from the dropdown of the *Canditate Name* column.

As in the multiple representations section, it is recommended that you look at the multiple functions to find that which best shows likely duplicate records.

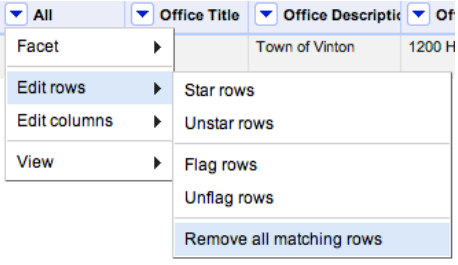
Unlike in the previous exercises we do not want to *change* values, we want to *remove* duplicates. To do this we first need to confirm that the data is duplicated. To discover this, hover your pointer over a cluster and then select the **Browse this Cluster** option.



Using the new window that pops up, we can then browse just that cluster and **star** any duplicated data that we wish to later remove. Once done, close the window or tab to return to the original dataset.



Do this for a number of duplicated records before closing the clustering screen.

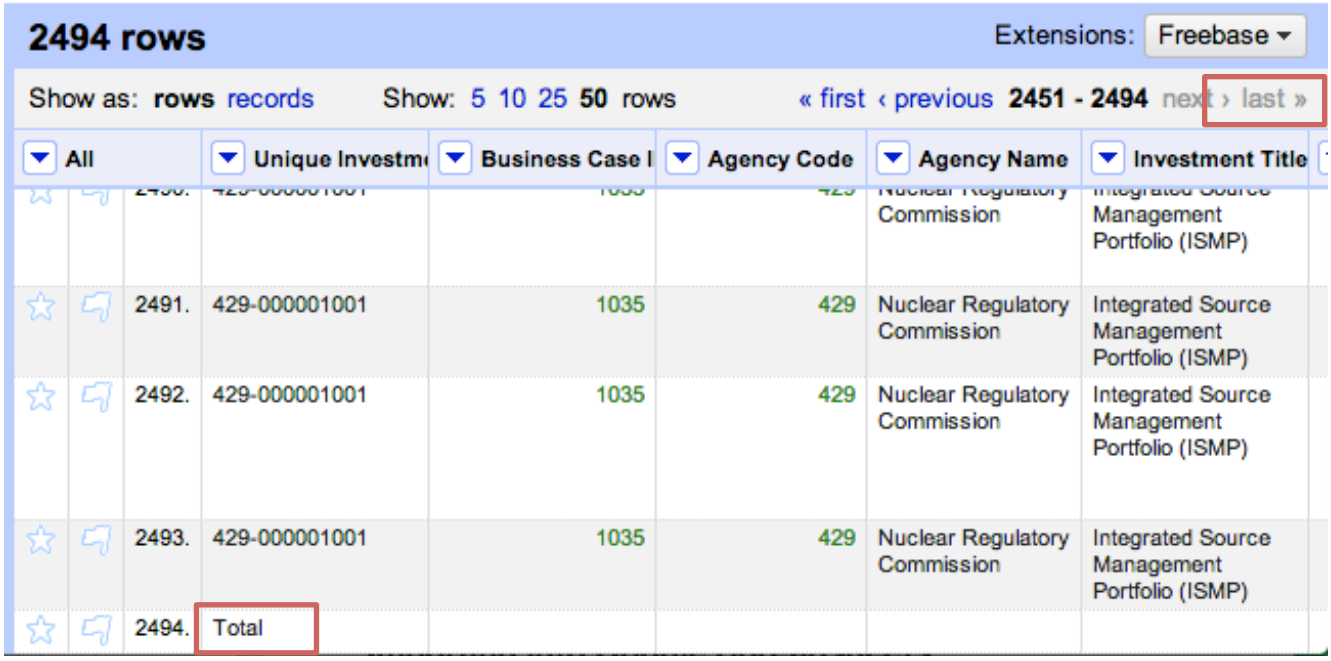


To view all the rows you stared apply a **star facet** to the *All* column, select the true values and then delete them by selecting **Remove all matching rows** from the **edit rows** menu. If you cannot see any stared rows, ensure that you don't have any facets currently applied.

4. Summation Records (Dataset 2)

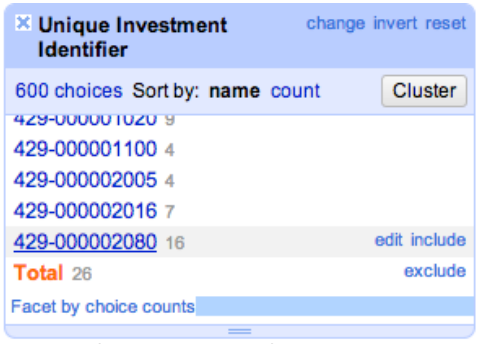
It is often the case that data exported from a spreadsheet application will contain summation rows and columns. While the columns are easier to spot, the rows are much harder in a large dataset.

A little tip is to browse right to the end of the dataset in order to see what the very last record is. This can be done in **Refine** by clicking the *last* button.



Let's start by staring the "Total" row for later removal. Now we know that they exist, we should check to see if there are any more rows and try to find what they represent.

Apply a **text facet** to the *Unique Investment* column and select all the rows that have the value "Total" and **star** these. While we are in the facet also note the row numbers where the total exists. As there are many of them, we might conclude that this one dataset is an export of many worksheets. Clearing the facet and browsing to one of the recorded row numbers allows us to gain an idea about how the data was represented in the various worksheets.



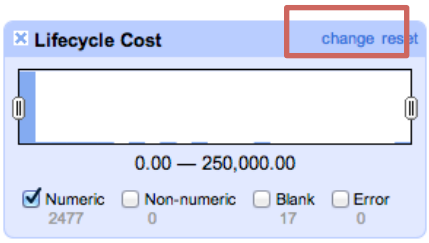
From the data displayed it looks like the totals are per agency. This can be confirmed by looking at how many agencies there are using another couple of facets. When happy that the summations are understood, delete the total rows such that they don't spoil the later processing.

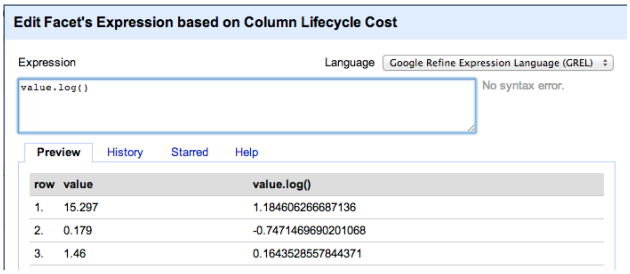
5. Mixed use of numerical scales (Dataset 2)

With the projects dataset being all about costing and budgets, we should probably take a look at the numerical data in these columns to see if there is consistent usage of units.

Applying a **numerical facet** to the *Lifecycle Cost* column is useful in some ways, but doesn't truly represent the distribution of values from a norm.

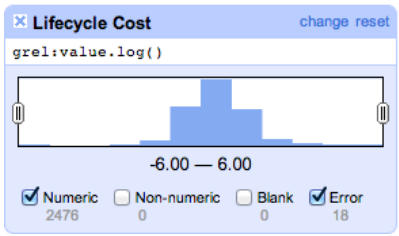
In order to distribute the values more evenly, click the change button. From the box that appears we can apply filters and programmatic changes to the values in the columns.



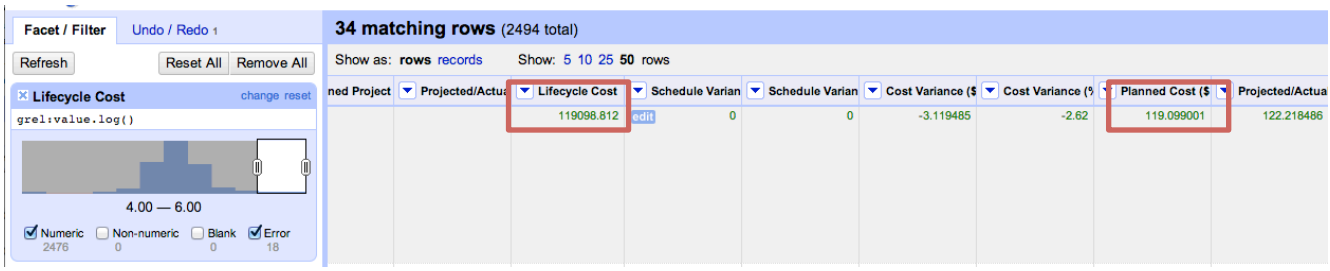


In order to more clearly display the distribution of our values we are going to change the values so we can view them on a log scale. This can be done by adding *.log()* to the end of our value.

Using this distribution we can now look at the values of the outliers to discover if there are errors in the dataset.



By looking at this data, as well as the column titles of other columns, it should be relatively clear that the units of this column are probably $M. There are many low cost projects, however there is also one 14 month project with a huge cost.



Looking at the different between lifecycle cost and planned cost should reveal the extent of the problem and allow it to be fixed.

Imagine the knock on effect this had with the totals!

N.B. While the totals rows were added to the data for the purposes of this exercise. The mistaken project cost of 117098 million existed in the original dataset!

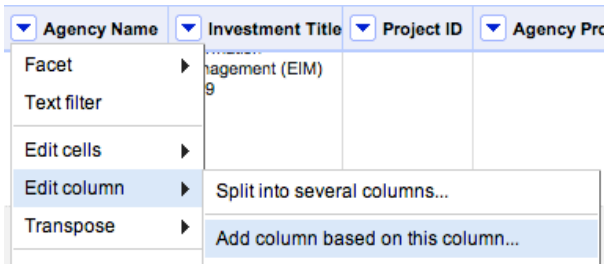
6. Redundant Data (Dataset 2)

During the summation records exercise it was discovered that the data appears to be grouped by Agency.

☆	👎	171.	005-000002376		1099	5	Department of Agriculture	Conservation Delivery Streamline Initiative (CDSI)
☆	👎	172.	005-000002376		1099	5	Department of Agriculture	Conservation Delivery Streamline Initiative (CDSI)
★	👎	173.	Total					
☆	👎	174.	006-000525200	edit	629	6	Department of Commerce	BEA Estimation Information Technology System (BEA-EITS)
☆	👎	175.	006-000525200		629	6	Department of Commerce	BEA Estimation Information Technology System (BEA-EITS)

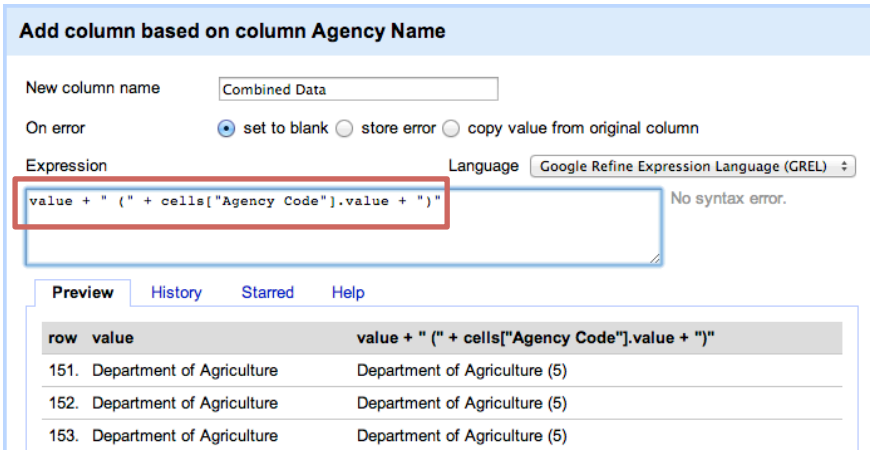
Looking at this data again, it should also be clear to see that we have an *Agency Code* and *Agency Name* columns. While it shouldn't matter that we have both pieces of data, redundant data can also lead to errors. Beneficially, redundant data can often be easier to fix; the more data you have, the clearer the fix is likely to be.

In this exercise we are going to check that the agency codes always match the name. In order to do this we are going to amalgamate the data in a single column and then apply a text facet.



From the *Agency Name* column select **add column based on this column** from the **edit column** menu.

This will pop up an expression editing box similar to the one we used in the numerical scales exercise. The default expression simply copies the data from this column to a new one. We are going to change this to copy the data from two columns into a new *Combined Data* column.



Once done, try applying a **text facet** to our new column to find and correct any errors that exist in the dataset.

As an interesting experiment, you could also choose to bring back the total columns and see if the totals correlated to one or more of your fixes.

7. Numerical Ranges – Dataset 3 (Advanced)

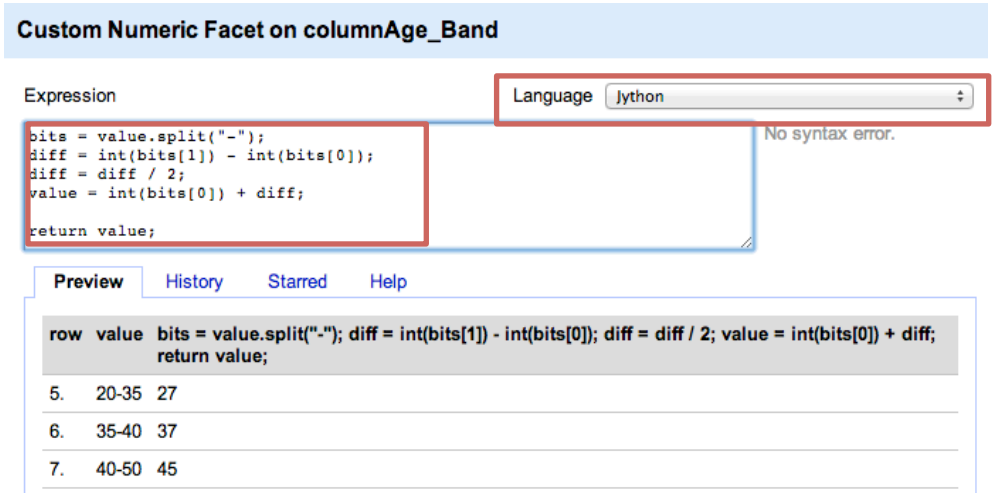
In anonymised data it is very common to split numerical data into ranges. However this can make processing and visualising the data a much bigger challenge. In the example below we can see both age range data (e.g. 25-30) and salary data (e.g. >25k).

GP_Type	Contract_Type	Country	Gender	Age_Band	Estimated_Popu	Effective_Retur	Average_Gross_
Salaried	GPMS	UK	Male	20-35	1100	700	>20k<30k
Salaried	GPMS	UK	Male	35-40	550	350	>30k
Salaried	GPMS	UK	Male	40-50	300	150	>10k<20k
Salaried	GPMS	UK	Male	50-65	250	100	>10k<20k

By applying a **text facet** to *Gender* and at the same time a **numeric facet** to *Average Gross Earnings from Employment*, you should be able to see that (in this dataset), men are earning more than women. Note also the character encoding error on the column titles, meaning the column titles give no indication of units.

In order to explore this further it would also be good to apply a **numeric facet** to *Age Band* and *Average Gross Earnings from Self Employment*, however the data in these columns it not numeric. We could try using the **to number** function under **common transforms**, however this does not work on this data so some other method needs to be applied. In this example we use the **expression editor** and the **jython** language to do some processing on the values.

To bring up the expression editor, choose **custom numeric facet** from the *Age Group* column.



In both this and the next example, the choice has been made to remove the ranges and simply change these into numeric values that represent the mid point (as a whole number).

To process the salary data is a little more complicated as we have lots of variations that need to be dealt with. Below is a piece of sample code to process the salary data.

```
value = value.replace('k','000');

if value[:1] == ">":
   value = value[1:];
if value[:1] == "<":
   value = value[1:];
if value[:1] == "=":
   value = value[1:];

bits = value.split("<");
if len(bits) < 2:
      return int(value);

diff = int(bits[1]) - int(bits[0]);
diff = diff / 2;
value = int(bits[0]) + diff;
return int(value);
```