Practical 1

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In this practical[1] we will focus on exploratory dataset analysis — an important first step before engaging in any Data Mining activities. We want get to know our data: find interesting observations, anomalies in data, and think about how to go about solving the task.

[1] **Important Practical Note**: If you cannot answer a task during the practicals fully, or feel unsure about your answer (even after the explanation), please ask! It is very important that you develop the correct intuitions for each of the points we discuss here. Sometimes they just don't 'click' by themselves; they require a lot of repeated practice and interpretation, and not every explanation works for everyone. We will be very happy to answer all your questions on the Discussion forum!

Refresher

Data Mining, Machine Learning, and all related fields have a special way of naming certain things related to data that are important to know by heart. This refresher will give you a short overview. Say we have a table (our data) describing ticket sales for concerts. See a small example below:

id	**gender**	**age**	**price**	**concert**	**genre**
01	f	21	40	AC/DC	hard rock
07	m	45	75	Ed Sheeran	acoustic
11	m	30	64	Depeche Mode	electronic
05	f	14	54	Hans Zimmer	instrumental

Table 1: Tickets instances containing customer & meta-data regarding their sales.

Each line (or row) of data is what we call an `instance`[2]. An instance usually refers to something concrete: a person, an animal, a song, a document, or in this case: a ticket. Instances are described by `features`[3], they tell you some (hopefully) characteristic information about these instances. Instances can be represented mathematically as a feature vector[4].

[2] Can also be referred to as an entry, observation, or data point.

[3] Also known as variables, or attributes.

[4] For the first instance above, this would be noted as:

$$\vec{x}_1 = \langle 01, \text{f}, 21, 40, \text{AC/DC}, \text{hard rock} \rangle \tag{1}$$

Where $\vec{x}$ is the vector, and subscript 1 the index.

Interpreting Features: Continuous vs Discrete

This doesn't simply work, however. In general, we want to be able to do calculations with these data. As such, features with what we call strings (letters) cannot be used in their raw form (e.g. `f`, `AC/DC`). For the sake of simplicity, we will get rid of the concert and genre features for this example. The gender variable can be recoded to 0 for f and 1 for m. So, we will get:

$$\vec{x}_1 = \langle 01, 0, 21, 40 \rangle \tag{2}$$

Now, the remaining 4 features also require a bit of interpretation. We distinguish between `continuous` features and `discrete` features. Continuous features are real valued and can be within some range, whereas discrete features are finite, and are usually associated with some label or category. In our example, `id`, `age` and `price` are all considered numeric (technically, they are all `ratio`). Gender can either be `binary` feature (0 = f and 1 = m), or other gender identities might be added, making it `nominal`. See Figure 1 for further info.

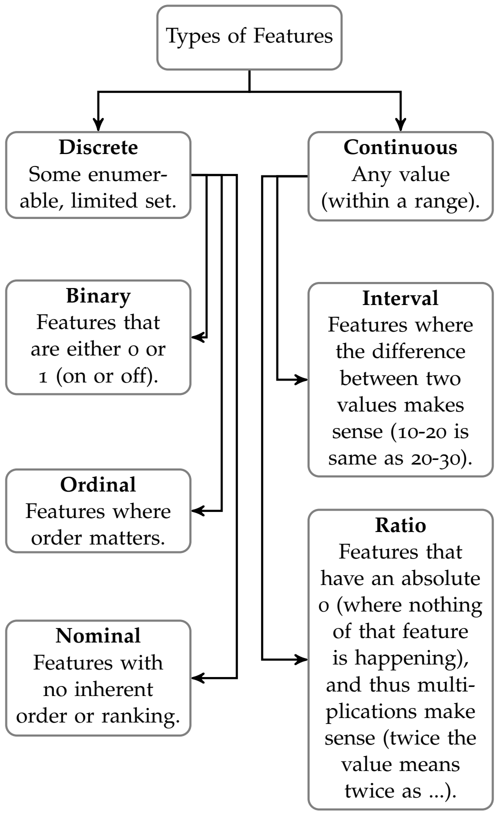

Types of Features
Discrete
Some enumerable, limited set.
Continuous
Any value (within a range).
Binary
Features that are either 0 or 1 (on or off).
Interval
Features where the difference between two values makes sense (10-20 is same as 20-30).
Ordinal
Features where order matters.
Ratio
Features that have an absolute 0 (where nothing of that feature is happening), and thus multiplications make sense (twice the value means twice as ...).
Nominal
Features with no inherent order or ranking.

Figure 1: Overview of the different types of features.

Feature Spaces

THE BEAUTY OF USING THIS NUMERIC REPRESENTATION is that each instance can be represented as a point in a space (or n-dimensional graph). So say that we plot the age on the x and price on the y-axis for some instances, our feature space as this is called, will look like Figure 2. This is a 2-dimensional space (with 2 axes). A bit more fancier 3-D space can be in Figure 3. However, we have 4 features - so this would have to be plotted in a 4-dimensional space. Unfortunately, we as humans can only see as much as 3-dimensions, so there's no way to show you how our actual feature space would look like (even colors and shapes will only get us so far). Luckily however, mathematical functions can handle this!

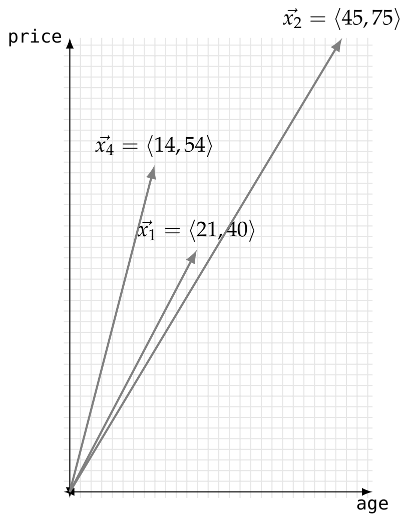


Figure 2: Vector space representation of Table 1.

Understanding your Data

YOUR FIRST STEP AS A DATA SCIENTIST (as frequently repeated in the lecture) is to *know* your data. Everyone can learn to fire up a program and click a few buttons, or write a few lines of code. It is your task, however, to understand this data and generate creative insights and be able to communicate these (in the form of a scientific paper or presentation). It is therefore important to know the possibilities and limitations of your data. The first dataset we'll be working with is the following. [5]

Please make sure you understand the dataset and the task **before** beginning!

[5]

Information	task	data
Data	raw	github

Setting up Jupyter

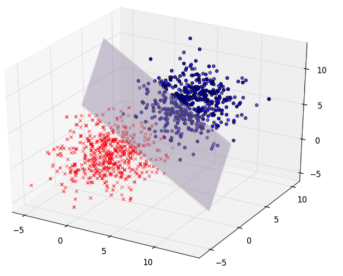


Figure 3: A 3-D representation where classes are coloured.

OPEN UP JUPYTER[6] and do the following: Open a new notebook using File › New › Notebook and start with inserting your ANR in the first cell (see Figure 4[7]), then switch the cell from `code` to `markdown` (for typing) by switching in the toolbar (Figure 5). Finally, you can insert new cells below using the + icon. Alternatively, while having your cursor active in a cell, press Esc to deselect it, and then b. You can either run a code cell, or render a Markdown[8] cell, by pressing ctrl/cmd + Enter.

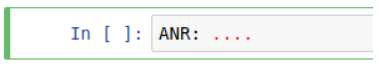
Now, let's get started, we're first going to create a cell with a few handy tools for the notebook. The first line `%matplotlib inline` makes sure that whenever there's a plot, it is displayed in our browser (otherwise it would just output some text). The other lines import the 'warning' package and disable some warnings from Python (pandas sometimes throws warnings for functions that will not work in some new version and such). These clutter our notebook, so we don't want them[9]

```
%matplotlib inline

import warnings
warnings.simplefilter(action='ignore')
```

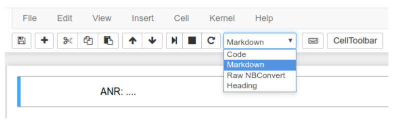
Now, we want to load `titanic.csv`. A small explanation of the directory: all our data is located in `/srv/data-mining/data/`. When inputting this directory, when you place your cursor at the last `/` and press ↹ / Tab, you can see the dataset directories to choose from (`Housing` and `Titanic` should be among them). If you select the directory from the drop-down menu and then press Enter and then ↹ / Tab again, you will see the dataset files.

We shorthand pandas (version 0.25.2) to `pd` and then load the `.csv` file into our `DataFrame` using `read_csv`. I will be providing links to the documentation of the objects and functions that we're using. Here you can see information regarding the `parameters` that a function takes. They are basically 'options' for a certain function. As you can see, `read_csv` has `index_col`, but also for example `sep`, which—if you read the documentation—can be used to indicate the `.csv` file `delimiter`. 'Delimiter' here means the character separating the values in our `.csv` file (by default it's set to `','` which is according to the format of our file). The index column is used to **uniquely** identify all your instances (usually with a number). The Titanic dataset has an actual index column, namely `PassengerId`. However, as it is unique for every instance, we don't want to use it as a feature anyway (think about why).



```
In [ ]: ANR: ....
```

Figure 4: ANR: ....



ANR: ....

Figure 5: Switching to Markdown. + shown in menu bar.

[6] `https://jupterlab.uvt.nl/`

[7] This looks a bit different in Jupyter Labs, but the menu parts are still there somewhere.

[8] Markdown is actually a pretty handy standard for formatting text. It's easy to practice within Jupyter.

[9] **Important Note**: **Save often!** The servers can be unstable. This prevents wasted time and (potentially) headaches.

Finally we store our dataframe in what's called a `variable`; a container with a name that we store our data (or any other object) under. Here, I call it `df` for dataframe. If we put this variable name on the last line in Jupyter, it will output the contents of the variable (in this case, our data). As such[10]:

[10] Please keep in mind that each dark block of code is supposed to be a new cell! Read back up if you forgot how to create those.

```
import pandas as pd

df = pd.read_csv('/srv/data-mining/data/Titanic/titanic.csv',
                 index_col='PassengerId')
df
```

Now let's get into some of the operations that we can run on our `DataFrame`. If you search the DataFrame documentation for `Methods`, they are all listed. These are all click-able, where more of their functionality is explained. It also short-lists the parameters of the function, if they are in between brackets (`[like,so]`), they are optional. The first one we'll be using is `count()` (that, as you can see in the docs, only has optional parameters). Let's try:

```
df.count()
```

When you put a function on the last line of a cell without a variable to store it in, this will make Jupyter also show the output of the function (like above).

Interpreting Raw Data

GIVEN THIS NEW INFORMATION try solving the following tasks. If we take a quick peek at the Wiki (link), we get some rough numbers for comparison[11].

[11] "Titanic had around 885 crew members on board for her maiden voyage.[95] Like other vessels of her time, she did not have a permanent crew, and the vast majority of crew members were casual workers who only came aboard the ship a few hours before she sailed from Southampton.[96]
Titanic's passengers numbered approximately 1,317 people: 324 in First Class, 284 in Second Class, and 709 in Third Class. Of these, 869 (66%) were male and 447 (34%) female. There were 107 children aboard, the largest number of which were in Third Class.[105] The ship was considerably under capacity on her maiden voyage, as she could accommodate 2,453 passengers—833 First Class, 614 Second Class, and 1,006 Third Class."

Task 1

- How much of the data are we missing?
- Do you see any features that you do not understand the values of?
- Which information could we potentially use to determine the crew of the Titanic in this dataset?

Solutions for all tasks are listed at the end.

We can try practising parameter-use a bit by trying the `axis` parameter to get column-wise counts rather than row-wise. As you can see from this line in the docs:
`DataFrame.count(axis=0,level=None, numeric_only=False)`
Axis is set to `0` by default.

```
df.count(axis=1)
```

Solve the difference between row-wise and column-wise counts for yourself. Also note that when getting any sort of counts for rows, they are always listed together with their index (`PassengerId`). We can see which passenger paid how much fare by selecting a specific column. This is done with:

```
df['Fare']
```

If we'd like to add the names to the output, we can list them like so:

```
df[['Name', 'Fare']]
```

Let's try aggregating some data. We're interested in how many passengers were in which economic class. Note that when subsetting our `pd.DataFrame` object to only a single column, it actually turns into a `Series`. These have different methods (functions) than Dataframes. Try `value_counts()`:

```
df['Pclass'].value_counts()
```

We can also aggregate even more 'complex' levels. Let's try grouping by Sex using `groupby()`, which we simply add in between our previous line:

```
df.groupby('Sex')['Pclass'].value_counts()
```

Just to quickly walk you through the steps: `groupby` splits the entire dataframe between sexes (so all feature values get divided between male and female). Convince yourself of this by running:

```
df.groupby('Sex').count()
```

Notice that `count` is used here again, because `groupby` returns all columns in the Dataframe, so the object is still a Dataframe (not a Series). This in contrast to the line before, where we add `['Pclass']` to only select the class feature (turning it into a Series, because only one column). For that one, we'd apply the `value_counts()`, as you can see. So, important take-away: always think if you're working on more than one column (dataframe), or just one (series), and see which methods you can use accordingly. Now we can safely go into exploring more methods.

Visualization

PANDAS WORKS WELL for selecting (sub-setting) and plotting different entries within a dataset. We'll first look at a way to visualize certain feature distributions using **density plots** (see Figure 6, and see if we can group them by `Survived`. For all the features that we inspect, you will see if this influenced whether people survived the Titanic yes or no. Say that we'd want to check this for `Fare`, the first step would be:

```
df.groupby('Survived')['Fare']
```

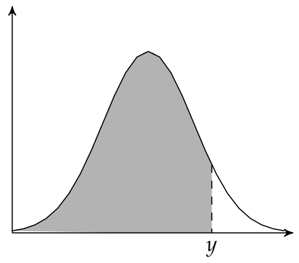


Figure 6: Density plot.

Both DataFrames and Series have a `plot()` method, with many possible parameters. You're free to check them out, for this we'll be using KDE (Kernel Density Estimation, or density plot). We make our line look like this:

```
df.groupby('Survived')['Fare'].plot(kind='kde', legend=True)
```

The default plots in Pandas don't look too fancy (granted, it's not a plotting library, this is just convenient functionality). We can alter this somewhat by for example:

```
import matplotlib.pyplot as plt
plt.style.use('ggplot')
```

Try running the plot again! Now, if you start changing around the features, you'll notice that some aren't compatible with density plots (they throw an error). This is because they are discrete, and therefore don't have a density estimation. You can use bar plots for these:

```
df.groupby('Survived')['Sex'].value_counts().plot(kind='Bar')
```

You should be able to figure out why we didn't include `legend` here. If you tried age, you see the warning `array must not contain infs or NaNs`. If you look at the very first `pd` table dump, you'll notice there are `NaN` ages (Not a Number). These are missing values. We can fix this with overwriting the age feature:

```
df['Age'] = df['Age'].fillna(0)
```

Here, we fill the NaNs with 0. Now, when interpreting the results, take into account that zeroes are actually NaNs.

You can up the complexity of the `groupby` function by stacking more features as a list, like so:

```
df.groupby(['Sex', 'Pclass'])['Survived'].value_counts().plot(kind='Bar')
```

You can also show the counts above in a table when removing `.plot(kind='Bar')`, if you replace `value_counts()` with `mean()` you get the averages for each group split, etc. Using these plots and checking the table outputs you can answer the following questions:

Figure 7: Hint from the movie.

Task 2

- Find two features where a certain group has a noticeable high mortality rate.
- Explain why this is the case with your knowledge of the dataset (having seen the movie might help, see Figure 7).

Distributions are pretty straight-forward to interpret; the visualization between two features is simple and effective. However, it also limits displaying interaction between several features (e.g. if young males tended have lower survival rates than females). For this, we can use **scatter plots** (see Figure 8). In pandas, you need to set an x and y label, like so:

```
df.plot(x='somefeature', y='someotherfeature', kind='scatter')
```

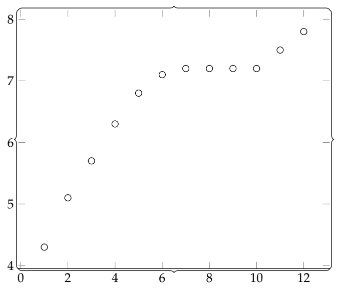


Figure 8: Scatter plot.

To stack multiple subsets in one plot, and give them different colors, we have to select them from the DataFrame based on some condition. We can do this for example for `Survived` with the following piece of code:

```
died_subset = df[df['Survived'] == 0]
live_subset = df[df['Survived'] != 0]
```

To break this down, the inner part (`df['Survived'] == 0`) returns the index numbers (that's where they come in handy!) where the value of `Survived` was equal to (==) zero (so the people who did not survive). The outer part `df[....]` then receives those index numbers, and returns a DataFrame with only the instances that met this condition of `'Survived == 0'`. If we want to do the inverse, we simply use `!=` (not equals), or, alternatively `== 1`. We can plot these different subsets by generating to plots, storing the first in a variable, and passing that along to the second plot.

Like so:

```
ax1 = died_subset.plot(x='somefeature', y='someotherfeature',
                       label='Died', color='red', kind='scatter')
ax2 = live_subset.plot(x='somefeature', y='someotherfeature',
                       label='Survived', color='green', kind='scatter',
                       ax=ax1)

ax2  # to output
```

Now notice that we're adding two new parameters here, one to label a specific subset in the legend[12], and the other to color the instances of the specific subset differently. We can also add an `alpha` parameter to determine transparency of the dots (e.g. by setting that to `0.5`).

[12] We didn't have to do this before, as this was encoded in the values, here it isn't.

Task 3

- Set `Sex` to x, and `Pclass` to y. What can you conclude?
- Set `Age` to x, and `Fare` to y. Do these features correlate?
- Split the above plot by `Survived`, do you see a pattern in the data?

Testing Hypotheses

If you followed through all above tasks, you now hopefully developed some intuition regarding which features might have a relation. The Titanic was a pretty interesting reflection of society around the 1900's. It opens up some potential for statistical analyses and some richer measurements. We'll look at boxplots for this section, and some very basic pointers on how to run stats in Python.

Pandas provides the usual boxplot annotations for the mean, median, standard deviation, min, max, (if you need a refresher on these, read: link, see Figure 9) and SciPy provides a statistical test for a set variable, between the classes of the provided subgroup. Through this, you can test if for example `Fare` had an effect on your survivability. Boxplots have a `column` parameter to select features (should be in a list format), and `by` to group. So you can do something like:

```
df.boxplot(column=['Fare'], by='Survived')
```

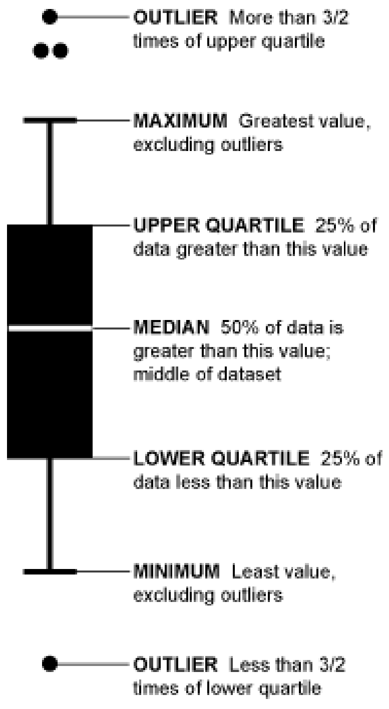

OUTLIER More than 3/2 times of upper quartile
MAXIMUM Greatest value, excluding outliers
UPPER QUARTILE 25% of data greater than this value
MEDIAN 50% of data is greater than this value; middle of dataset
LOWER QUARTILE 25% of data less than this value
MINIMUM Least value, excluding outliers
OUTLIER Less than 3/2 times of lower quartile

Figure 9: Boxplot cheat sheet.

Then finally, `scipy.stats` also has an implementation for `ttests` and the like. Given that we have a lot of unbalanced groups and some binary data, we're not going to go in the statistical mess required to say anything sensible about these here. Just know that the tests are available. To round off the practical:

Task 4

- Determine a likely ticket price to survive the Titanic.

Solutions

Task 1:

- Given the Titanic Wiki quote, we see that there were 1317 passengers. So we're missing $1317 - 891$ passengers (see `df.count()`).
- This is personal: if you aren't sure, look at the docs what they mean, and **especially** what the values are!
- Well, if you read the quote carefully we know that it's highly unlikely that there's any crew in the dataset. Some features could however be: Fare (if that would be 0), or Embarked (see Wiki).

Task 2:

- `Pclass` and `Sex`.
- Women and children first, ice hit the boat in the lower deck (lower class). Most of the latter drowned before even making it to any lifeboats.

Task 3:

- Not more than that they are two discrete features and scatter plots only work for continuous ones[13].
- Not strong enough to clearly see a visual correlation. You can test it using `scipy.stats.pearsonr`. See below for code.
- There's a few observations we can make, but not necessarily very clear patterns. It looks like from low-fare payers over 40, the majority seems to be a non-survivor. We can also see that the high fare payers generally survived (there's even a few super high outliers with 500+ fare, they survived).

[13] See first bit of code below to fix the error pandas throws.

```
df['Sex'] = pd.get_dummies(df['Sex'])  # convert numerical to discrete

# make sure to reconstruct the subsets based on the Dataframe with the
# now fixed variable encoding
died_subset = df[df['Survived'] == 0]
live_subset = df[df['Survived'] != 0]

# plot here


from scipy.stats import pearsonr

pearsonr(df['Age'], df['Fare'])  # run df['Age'].fillna(0) before!
```

Task 4:

- With paid Fair upwards from 50, you're an outlier if you die.