# D1

Hello, I am going to present to you our progress on our Data Mining project: Energy Consumption in Oulu.

# D2

We based our work on the following problematic: How do the buildings' characteristics (their floor count, their gross area, or their location) impact their yearly energy consumption and can we cluster some different consumption profiles (and do we get similar results between the first analysis and the clustering)?

# D3

## Data set

The data is composed of 2 documents:

One which is the buildings’ metadata, that describes their characteristics: it gives some information about their floor count, their gross area or the year of construction.

The other is the buildings’ hourly energy consumption records, which describes the recorded heat and electricity consumption on a certain time window. Those records have to be retrieved from an URL.

# D4

So this is a metadata table example with some characteristics of different buildings, some of them or not visible here, but there are 16 of them in total such as...

And to merge these 2 documents, we can use a common attribute, which is the buildings’ id. We simply will have to apply a join function to do so.

# D5

Next, we have the consumption records, you can see the property id again and the consumption value and measure type, and the time where it has been recorded.

# D6

As we could expect, the dataset has to be cleaned for the following reasons.

## Data Cleaning

Some outliers were noticed, although it doesn’t impact the data that much.

However, a lot of data is missing, some is redundant, untranslated or the used format are not optimal.

# D7

## Missing Data

By exploring the dataset, I quickly noticed that some records were missing. Indeed, on the 536 buildings in metadata, only 286 actually have energy consumption records. So, we have to completely ignore about half of the buildings.

# D8

## Data transformation

The metadata don’t need that much transformation as it is just a list of characteristics, the intended uses had to be translated. However, some information is missing for a lot of buildings, we can only manage them downstream. For example, a lot of building’s floor count is 0. And so, it is hard to predict why is that so, but if we look at its records, most of the 0 floor count buildings have invalid or mostly missing records so we can not really study them but neither can we be 100% sure that they will be uninteresting. We will see that in the next slides.

And for the consumption’s records, they also needed quite some transformation. First, the energy type (heat and electricity) had to be translated (go D5). The time was also noted as 4 different attributes (hour, day, month and year) which make the records hard to classify chronologically. So, I decide to use a datetime library which allow us to compare the times easily. The URL with which we retrieve the records is taking years as time parameter and so it had to be narrowed as an hour/day/year format.

# D9

This is what the data frame looks like after the transformation, the consumption measure is now in English and the time format is now compact, on only one column.

# D10

## Feature extraction

An important objective of our project is to look for correlation between building’s characteristics and their energy consumption.

So, this is why I found interesting to split the buildings’ characteristic in 2 or 3 different types of features to search for these possible correlations:

Categorical features: Intended uses, postal code district name

Semi-continuous features: The gross area or the volume

Some in-between features, the Discrete features: Floor count, Year of construction

I think this last one is a bit tricky because some of its characteristics can be classified as categorical or semi-continuous according to the wanted precision. For the year of construction, you could want the average consumption for each year (continuous) or for each decade (categorical)

# D11

### Categorical features

I started with the categorical features as so:

First, we need to create a list of characteristic categories, here we are looking at the building’s intended use. For example, we will have this list with educational buildings, Kindergartens and Health centers.

Then we browse this list and retrieve the average energy consumption of a certain number of buildings per category by merging the metadata and the consumption records by using the property id. At the same time, we are checking if we can actually retrieve the consumption, it happens that the records are partly missing or invalid (for example, here we can see that heat measurement is missing for the selected educational buildings).

Finally, we group these means by category to have a wider viewpoint of energy consumption by category, here by intended use.

And we can display these results with graphs to visualize them.

# D12

So here, on this new example, we can see the proportion of the buildings we couldn’t retrieve an average consumption measure (in blue), classified by floor count. The gray bars indicate the remaining valid data. And so, this graph allows us to know if the results are consistent or not. If they are too much missing data, the results could actually be inconsistent.

# D13

And finally, the average consumption visualization. Here can see the average heat (in orange) and electricity (in blue) classified by floor count. And we can clearly see a tendency to consume more energy as the floor count increases. Also notice that we went from a sample of 136 records to 60 valid samples.

# D14

But for now, I will show you the most interesting graphs I have created for now:

First, on these 3 graphs, I noticed that the size of a building linearly impacts the general energy consumption as we can see on these three graphs: the more building’s gross area, volume or floor count is, the more energy it consumes.

# D15

I also realized that some intended uses have more impact, for example, here the health centers clearly show a difference with the other buildings. Contrarily as kindergartens or storage buildings.

# D16

And finally, the year of renovation also shows some interesting results: buildings which were renovated between 1998 and 2009 are more consumptive than the buildings renovated before and after this time window.

# D17

## Next steps

About the next steps.

Now that I studied categorical features, I have to find a way to split the discrete and semi-continuous features which I already almost finished as you could see.

I will also have to narrow down the consumption average to a monthly or yearly basis to have a more precise idea of the building’s consumption changes over time and according to their characteristics

And finally, I will have to continue to compare the characteristics correlated impact in more details. For example, are certain consumptive intended use buildings are bigger than the others, in which district are they etc..

# D18

I am currently working on it but it would look the final result could look like something like this graph. A curve for every characteristic category or interval. Here for two intervals of gross area (one is between 50 and 300 square meters and the other on between 300 and 500). And instead of simply print the total hourly records like in this previous slide (D9), we reduce the time window to a monthly average, and this what it would look like. This would allow us to have a more precise understanding of the building’s consumption over time and according to their characteristics.

# D19

## Group work

We tried to share the work in independent sub-questions answering our problematic since it seems that we all have very different schedules and ways of working.

So, I did all the above presented work which is about data collection and basic data transformation and cleaning such as language translation and changing the wrong formats. I extracted the features as categorical and semi-continuous characteristics with the previous results I showed you. Thus, we can analyse the impact of the building’s characteristics on their energy consumption. And I am also responsible of the communication with our mentor as the creation of this presentation.

Arttu is charged of doing a spatial analysis of the Oulu building’s consumption over the city in order to observe the differences between districts and displaying it on an interactive map.

Mussadaq is trying to cluster consumption profiles. Starting by clustering energy consumption on a daily basis.

Mari is charged of writing the report and doing researches about related work.

And as I didn’t have the time to add my coworkers’ work as we have different schedules, I will let them introduce their work progress in more details.

# D20

## Conclusion

In a nutshell, our dataset is presenting interesting and complex challenges which can lead us to very promising results. There is quite a lot of missing data to manage and some data to clean and transform (like language translation and reformatting).

But we could already established that some characteristics have a clear impact on the energy consumption of Oulu’s buildings.

And we can already see some correlation patterns between characterisitcs, for example, in the district of Kaukovaino

# D21

Any questions ?