Capstone Project 1
Absentee Profiling

Andrew Liu

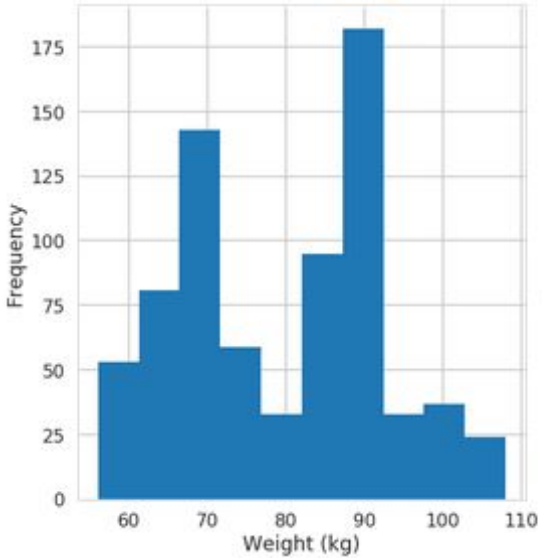
Proposal with Problem Statement

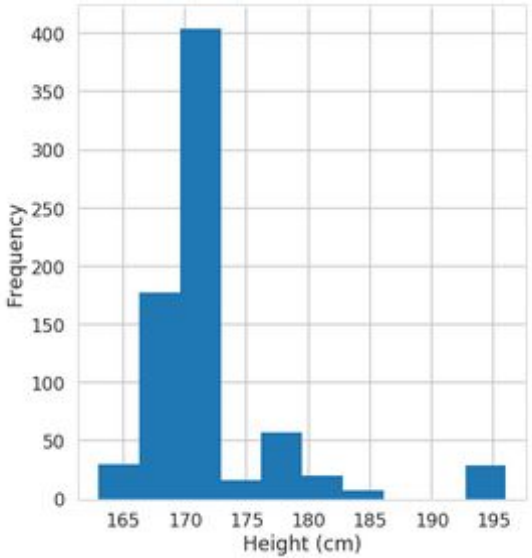
- The goal is to create a profiling scheme using predictor variables detailing absences from work, such as the type of illness, month of absence, and worker age.
- Provided by the UCI Machine Learning Repository and has already been acquired.
- We can use any clustering method (KMeans) to create clusters on our data. To select k we can use a variety of performance metrics like SS
- Once clustered, we can individually investigate each of the clusters to see if they intuitively make sense, and create labeling characteristics that define each of the clusters.
- The ID of the worker for each absence has been recorded, so we can also investigate each worker individually (36 workers) to see if there is a pattern based on worker (as opposed to each instance of an absence).

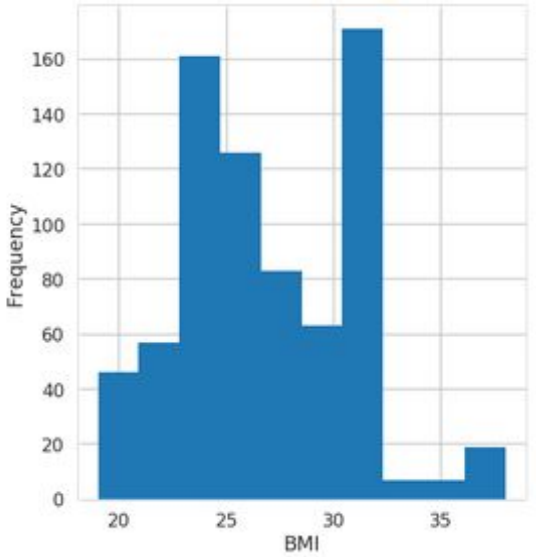
Data collection and wrangling summary

- The dataset was provided by the UCI machine learning repo, and was already formatted. No additional steps were needed to clean the data.
- A few of the entries for “month” were 0, so while the data wasn’t explicitly missing, the entry didn’t make much sense. The entries were left as 0, and were properly encoded as a row of 0’s when one-hot encoding was used.
- There were a few data entries that had uncommon values for a few of the features, but these entries were left as is to capture the variability in profiling, as there were only 740 entries in this dataset..

Distribution of Height, Weight, BMI



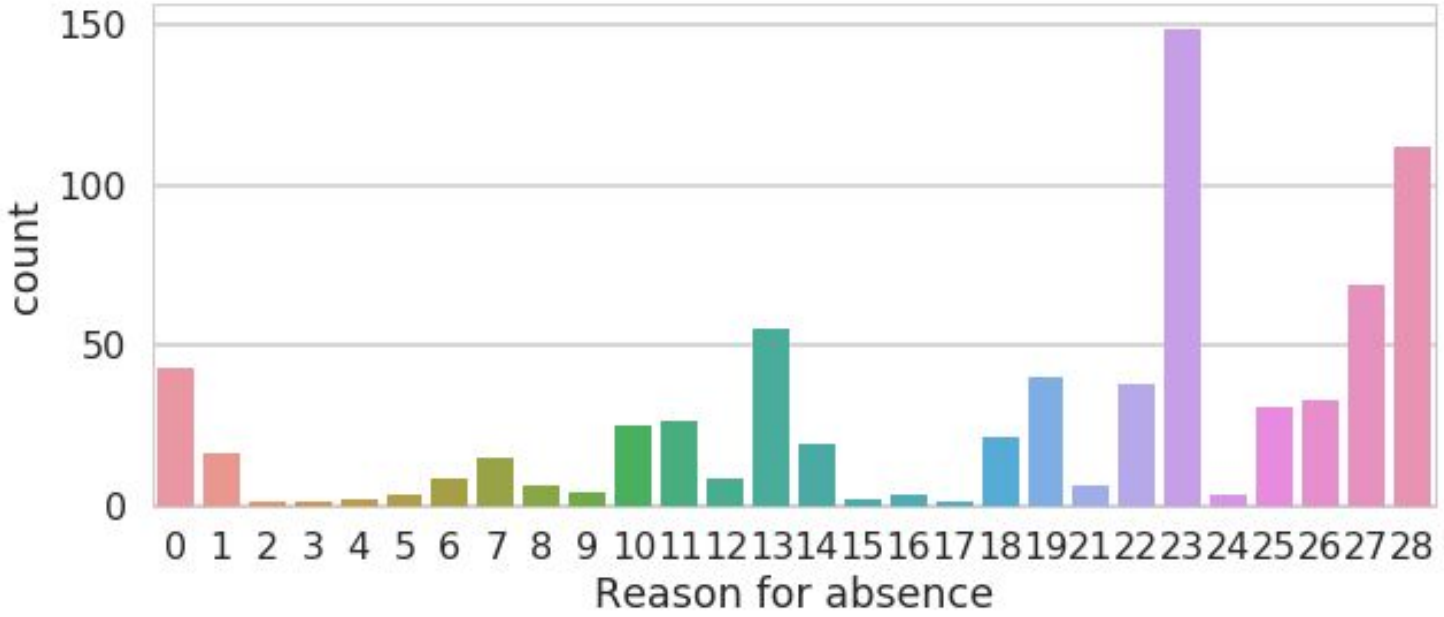




Distribution of Height, Weight, BMI

- Some of the distributions from the previous slide look a bit weird! (bimodal, skewed, etc)
- We expect things like height, weight, and BMI to be approximately normally distributed
- However, these histograms are a histogram of absences, not people, and although we believe the distribution of weights across all people to be normal, we shouldn’t expect the same from absences

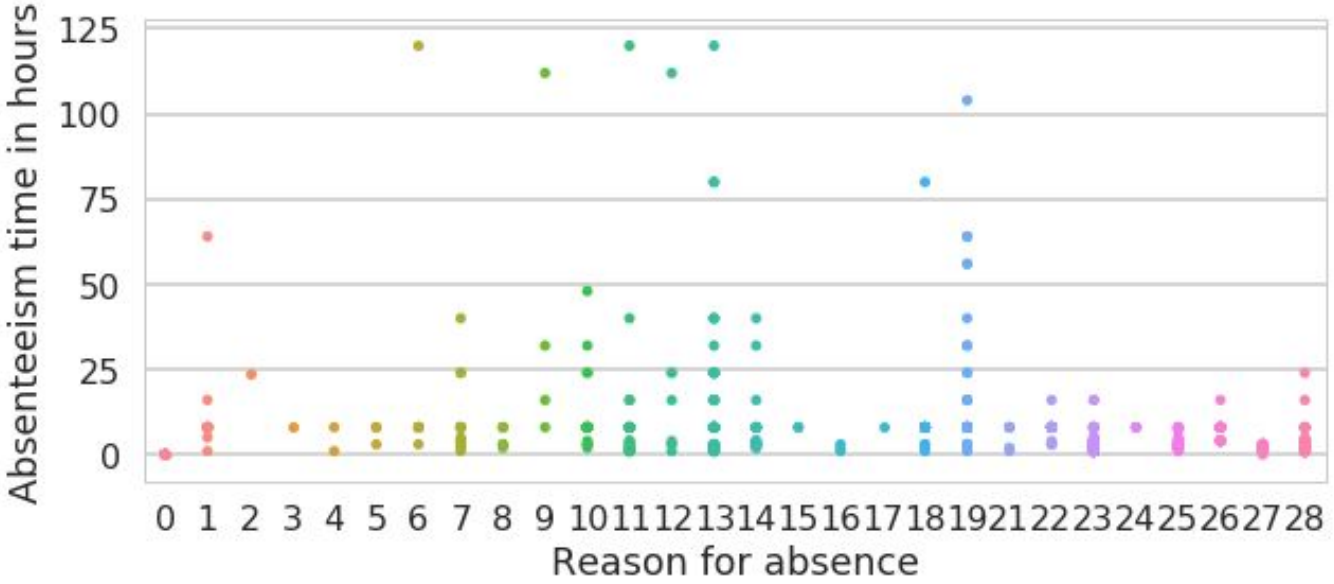
Distribution for Reason for Absence



Distribution for Reason for Absence

- Medical consultation(23) and dental consultation(28) are by far the most popular reasons given
- Physiotherapy(27), diseases of the musculoskeletal system and connective tissue (13), laboratory examinations (24) and unjustified absence(25)

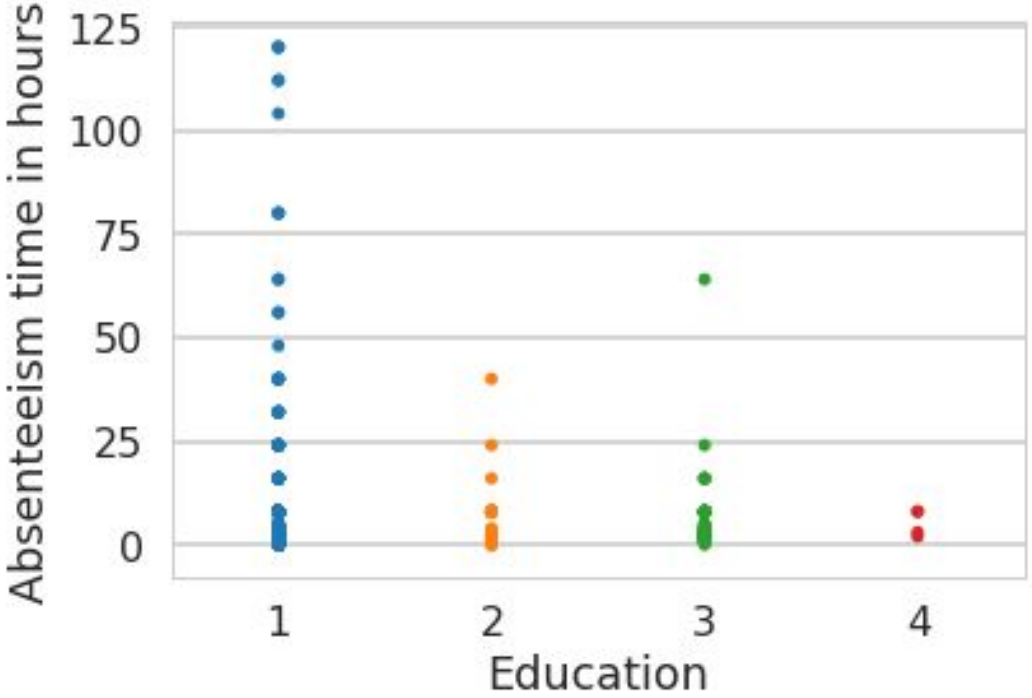
Absence Duration Based on Reason



Absence Duration Based on Reason

- The last seven reasons for absence (22 through 28) were not attested by the International Code of Diseases (ICD)
- Reasons 1 through 21 were attested by the ICD
- These last seven reasons had all absences take less than 24 hours, while the first 21 types of absences have lengthier occurrences

Relationship between education level and Absence duation?



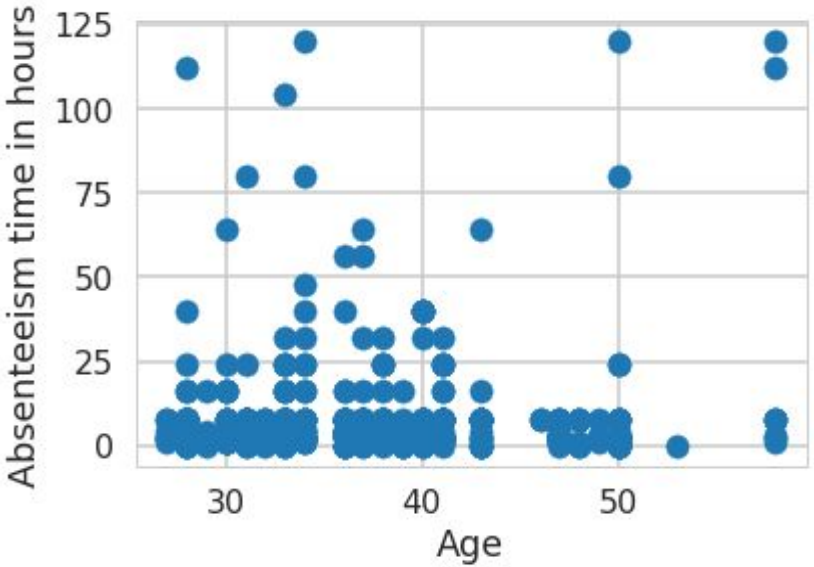
- Conduct a t-test to see if at least one of the group means is different from the others:

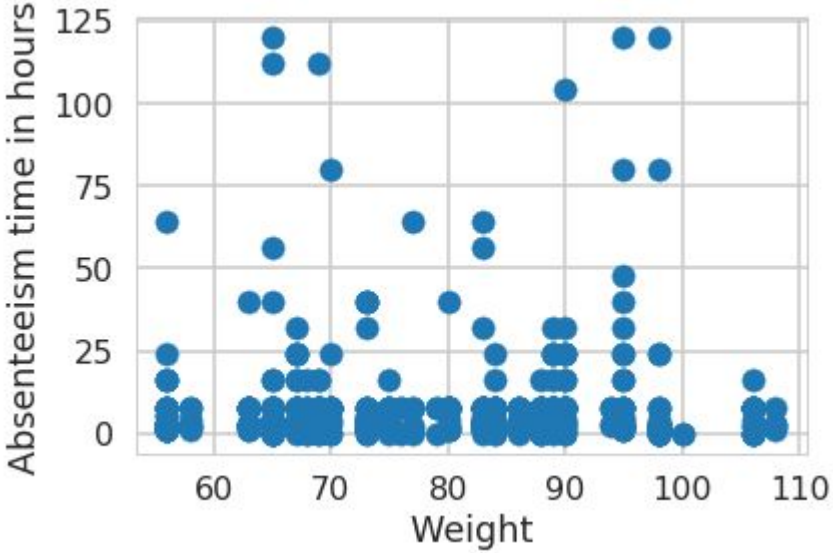
$$H_0 : \mu_1 = \mu_2 = \mu_3 = \mu_4$$

H_A : At least one of the means is different from the others

- T-test results: p-value of $3.43*10^{-28}$, which is less than our alpha of 0.05.
- Conclude that at least one of the means of the four different education groups is different from the others

How are other features related to absence duration?





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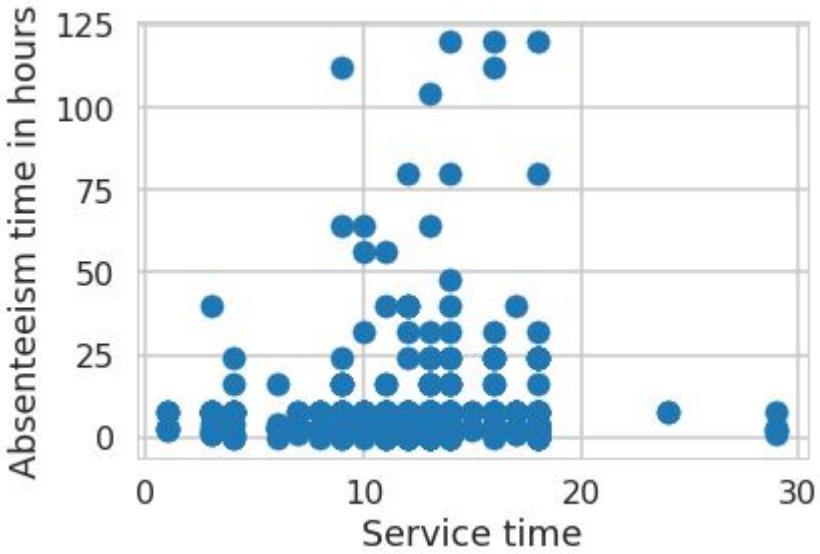
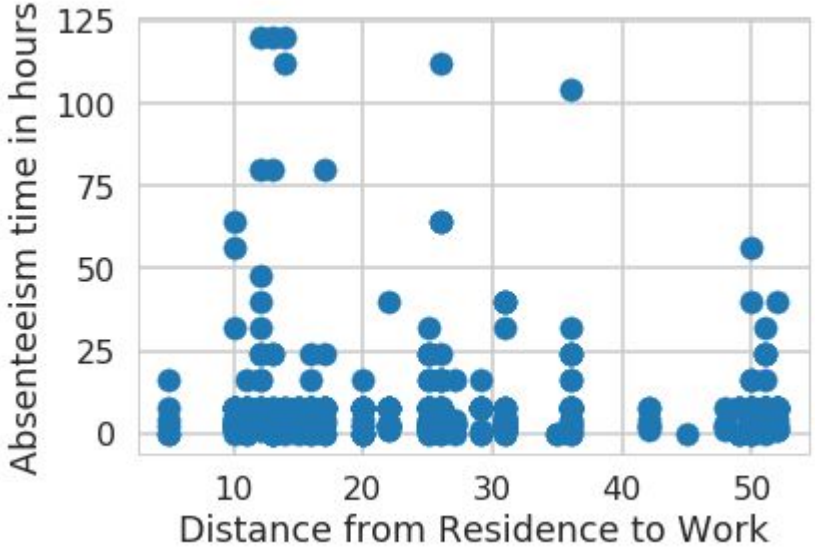




Linear correlation: Pearson correlation coefficients

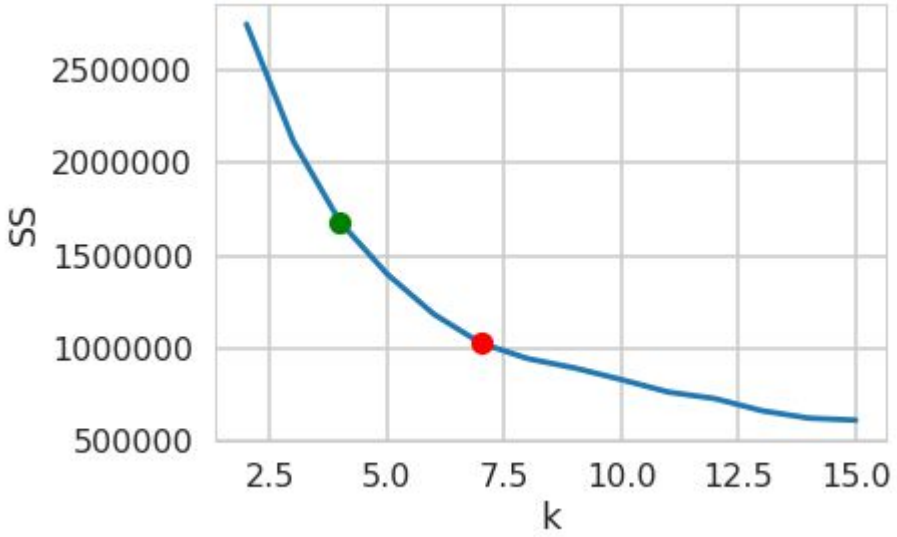
	Correlation Coeff with Absence Time	P-value(two-tailed)
Age	0.066	.074
Weight	0.016	.668
Distance	-0.088	.016
Service time	0.019	.605

Linear Correlation

- None of our proposed variables (age, weight, distance between residence and work, and service time) have a strong linear correlation to the absence time
- Do note that there may be other types of correlations (e.g. quadratic) that would better capture the relationships.

Profiling Absences

- Used k-means to create clusters of absences
- Looked at SS to select k
- Chose k = 4 in this case



Profiling Absences

- After forming the clusters, examined each of the clusters and tried to find some similarities among absences per cluster
- One-hot encoding used to handle categorical data
- Defining traits are listed below:

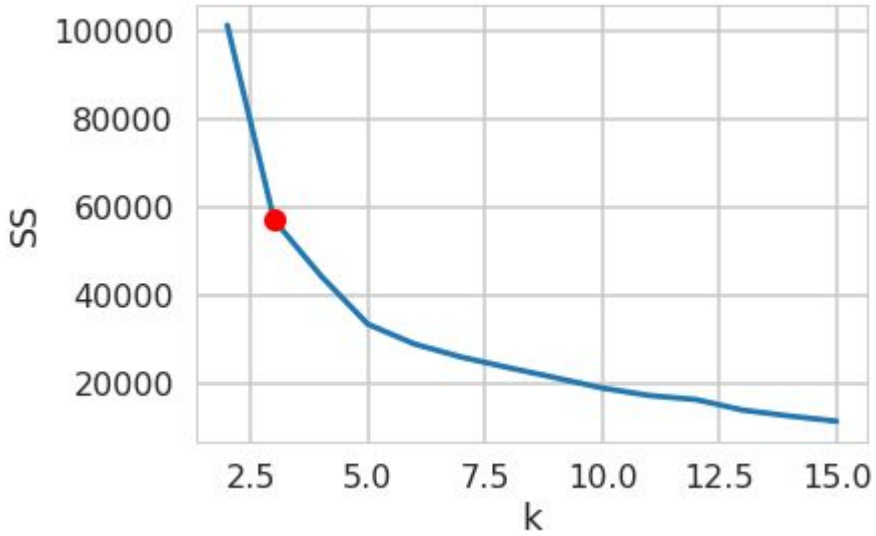
Cluster 0	**Cluster 1**	**Cluster 2**	**Cluster 3**
	Under 200 Transportation expense	Between 150 and 200 Transportation expense	At least 300 transportation expense
Late 20s	Late 30s to early 40s	Under 30 y.o	
Weighs right under 70kg	Between 80 and 90kg		
Has 1 Child	No Children		
Between 0 and 10 hours absent			At least 10 hours absent

Profiling Individuals

- Applied the same technique used to profile absences onto the individuals.
- If an individual had multiple entries, we took the mean (numerical continuous data) or the mode (categorical data)
- Again, one hot encoding used to handle categorical data

Profiling Individuals

- Used SS to determine k
- Picked k=3, as we had only 36 individuals



Profiling Individuals

- After forming the clusters, examined each of the clusters and tried to find some similarities among absences per cluster
- Defining traits are listed below:

Cluster 0	Cluster 1	Cluster 2
		Under 12 hours absent
High transportation cost	Low Transportation cost	Medium-priced transportation cost
	Heavier workers	Lighter workers
	Taller workers	Shorter workers
		Longer absences

Conclusions and Future Work

- Inherent problem with k-means is selecting a good k
- Approach also complicated by the number of feature variables added when one-hot encoding was applied to categorical variables: Almost 80 variables added!
- The “artificial” numerical 1/0 scheme provided by one-hot encoding isn’t ideal for k-means where variables are ideally continuous (i.e. can take on values more than just 0 and 1)
- Perhaps another type of ML technique (e.g. neural networking) is better suited for this type of profiling than k-means

Recommendations for the Client

- Transportation expenses plays a role in absence behavior. Typically more expenses is correlated with more time off.
- Absence behavior also predicted well by the reason of absence: many non-ICD attested reasons tend to have shorter absence durations than ICD-attested reasons