# MIE1624 Assignment 1 Predicting Kaggle Data Scientist Compensations

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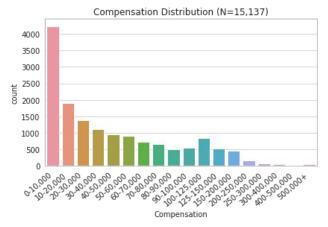
# Introduction & Exploratory Data Analysis

Goal: Predict annual compensation range in USD for a given data scientist given various features including: Gender, Age, Country, Education, Industry, Years Experience, etc

 $\rightarrow$  Ordinal classification problem since target is categorical with 18 ranges from 0-10k to 500k+

Raw Dataset: Kaggle Survey with 15,429 samples and 314 columns

Cleaned Dataset: 15,137 samples with a target label

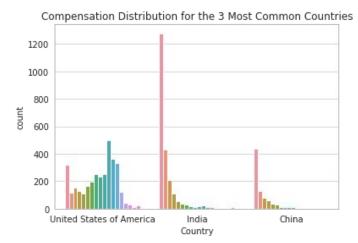


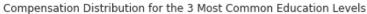
Note: Target variable is skewed to lower compensations

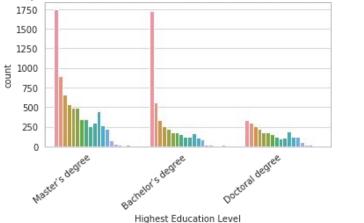
## **Visualizations**

#### Compensation is higher for those who:

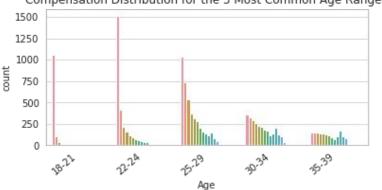
- live in America as opposed to India or China
- have a high level of education
- are older





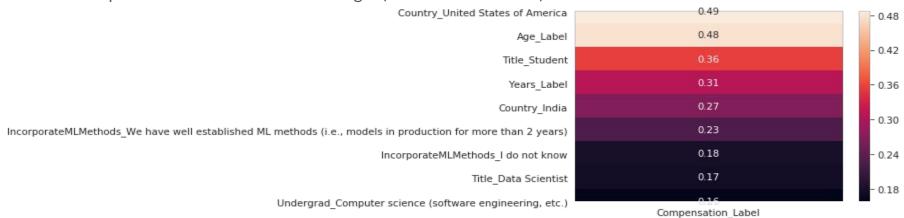


#### Compensation Distribution for the 3 Most Common Age Ranges



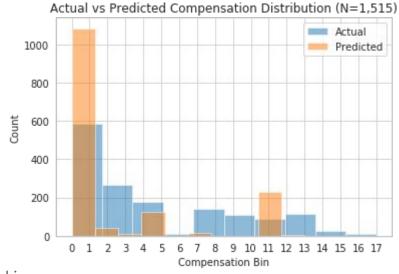
## Model Feature Importance

- Filled NaN values with 0 for existing binary features in the original dataset
- One hot encoded every country and industry since Logistic Regression can't interpret text directly
- Label-encoded compensation as well as Age and Years Experience to capture the ordered relationship
- Top 10 correlated features with target (absolute correlation):



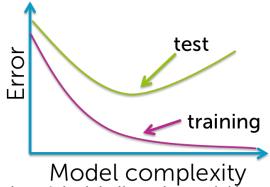
## **Model Results**

- Feature Engineering yields 425 available features
- Feature Selection done automatically with LASSO,  $C=0.1 \rightarrow 378$  features were kept
- 10 fold CV Grid Search yielded hyperparameters:
  - C = 0.001
  - Solver = newton-cg
- Optimal Logistic Model 10 fold CV performance
  - Average Accuracy (F1-score): 33.442%
  - Average Standard Deviation: 5.7%
- Clearly room for improvement
  - Model tends to over-predict the lowest compensation bin and is unable to accurately predict high compensation bins



## **Discussion and Future Work**

Overfitting or Underfitting?



- Since training set accuracy (34%) and test accuracy (32%) are close, I don't believe the model is overfitting
- Only way to verify underfitting would be to plot the Error/Accuracy vs. Model complexity
  - Low model complexity would cause underfitting → low values of C means the regularization strength is high
  - Error is composed of two components the squared bias and the variance (want to minimize both)
  - Use F1-score to measure accuracy since it considers both precision and recall

#### **Future Work:**

- Test more C values in the Grid Search and plot Error/Accuracy vs. Model Complexity
- Use PCA to reduce feature dimensionality or tune C for LASSO feature selection
- Reduce the cardinality of the target variable from 18 compensation bins to >10 bins
- Select a subset of data points (focus on a specific country or age bin)