



Feature Engineering and Data Preparation



Feature Engineering

- In the real world, not every data set is machine learning ready, we often need to perform data cleaning or try to produce more usable features.
- In this section, we'll work on the large linear regression data set to get it ready for a machine learning project.



Feature Engineering

- What is feature engineering?
 - Is the process of using domain knowledge to extract features from raw data via data mining techniques.
- But what does this actually entail?



Feature Engineering

- Three general approaches:
 - Extracting Information
 - Combining Information
 - Transforming Information



Feature Engineering

- Extracting Information
 - Imagine a dataset with visitor expenditure information for a bar.
 - We have a timestamp for each row:
 - 1990-12-01 09:26:03
 - In its current format, its very difficult to pass into a machine learning algorithm.



Feature Engineering

- Extracting Information
 - In its current format, its very difficult to pass into a machine learning algorithm.
 - There is no coefficient we can apply for a non-numeric data point:
 - 1990-12-01 09:26:03
 - In general for most algorithms we need to make sure features are float or int.



Feature Engineering

- Extracting Information
 - Instead we extract information
 - 1990-12-01 09:26:03
 - Year: 1990
 - Month: 12
 - Weekday or Weekend (0/1)
 - Mon:1,Tues:2, ... Sun:7



Feature Engineering

- Extracting Information
 - More complex examples:
 - Text data for deed of house
 - Length of text
 - Number of times certain terms are mentioned



Feature Engineering

- Combining Information
 - We've actually already done this with Polynomial Regression!
 - Recall advertising spend could have possible interaction terms to consider, so we could multiply them together.



Feature Engineering

- Combining Information
 - Could also combine extracted information:
 - New Feature:
 - 0 or 1 value indicating:
 - Both weekend and evening?



Feature Engineering

- Transforming Information
 - Very common for string data
 - Most algorithms can not accept string data (can't multiply a string such as "red" by a numeric coefficient)



Feature Engineering

- Transforming Information
 - Often categorical data is presented as string data.
 - For example a large data set of social network users could have country of origin as a string feature (e.g. USA, UK, MEX, etc...)



Feature Engineering

- Transforming Information
 - We can use two approaches here:
 - Integer Encoding
 - One-hot Encoding (Dummy Variables)



Feature Engineering

- Integer Encoding
 - Directly convert categories into integers 1,2,3...N



Feature Engineering

- Integer Encoding
 - Directly convert categories into integers 1,2,3...N

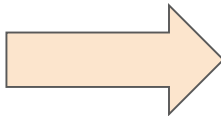
Country
USA
MEX
CAN
USA



Feature Engineering

- Integer Encoding
 - Directly convert categories into integers 1,2,3...N

Country
USA
MEX
CAN
USA



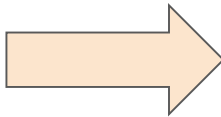
Country
1
2
3
1



Feature Engineering

- Integer Encoding
 - Possible issue is implied ordering and relationship (ordinal variable)

Country
USA
MEX
CAN
USA



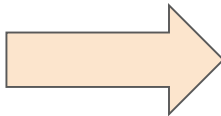
Country
1
2
3
1



Feature Engineering

- Integer Encoding
 - Here we see the implication MEX is twice the value of USA

Country
USA
MEX
CAN
USA



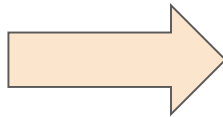
Country
1
2
3
1



Feature Engineering

- Integer Encoding
 - Here we see the implication CAN is three times the value of USA

Country
USA
MEX
CAN
USA



Country
1
2
3
1



Feature Engineering

- Integer Encoding
 - This may or may not make sense depending on the feature and

Country
USA
MEX
CAN
USA



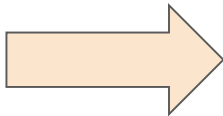
Country
1
2
3
1



Feature Engineering

- Integer Encoding
 - This may or may not make sense depending on the feature and

Spice Level
Mild
Hot
Fire
Mild



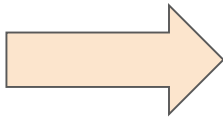
Spice Level
1
2
3
1



Feature Engineering

- Integer Encoding
 - Always carefully consider the implication of integer encoding

Spice Level
Mild
Hot
Fire
Mild



Spice Level
1
2
3
1



Feature Engineering

- Integer Encoding
 - Pros:
 - Very easy to do and understand.
 - Does not increase number of features.
 - Cons:
 - Implies ordered relationship between categories.



Feature Engineering

- One Hot Encoding (Dummy Variables)
 - Convert each category into individual features that are either 0 or 1



Feature Engineering

- One Hot Encoding (Dummy Variables)
 - Convert categories into individual features that are either 0 or 1

Country
USA
MEX
CAN
USA



Feature Engineering

- One Hot Encoding (Dummy Variables)
 - Convert categories into individual features that are either 0 or 1

Country
USA
MEX
CAN
USA



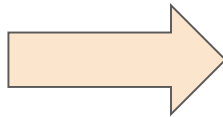
USA	MEX	CAN
1	0	0
0	1	0
0	0	1
1	0	0



Feature Engineering

- One Hot Encoding (Dummy Variables)
 - No ordered relationship is implied between categories.

Country
USA
MEX
CAN
USA



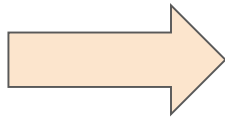
USA	MEX	CAN
1	0	0
0	1	0
0	0	1
1	0	0



Feature Engineering

- One Hot Encoding (Dummy Variables)
 - However we greatly expanded our feature set, many more columns.

Country
USA
MEX
CAN
USA



USA	MEX	CAN
1	0	0
0	1	0
0	0	1
1	0	0



Feature Engineering

- One Hot Encoding (Dummy Variables)
 - We can try to reduce this feature column expansion by creating higher level categories.
 - For example, regions or continents instead of countries.



Feature Engineering

- One Hot Encoding (Dummy Variables)
 - Using pandas `.map()` or `.apply()` can achieve this.
 - May require a lot of tuning and domain experience to choose reasonable higher level categories or mappings.



Feature Engineering

- One Hot Encoding (Dummy Variables)
 - Also must be aware of the “dummy variable trap”, mathematically known as multi-collinearity.
 - Converting to dummy variables can cause features to be duplicated.
 - Let's consider the simplest possible example...



Feature Engineering

- One Hot Encoding (Dummy Variables)
 - Consider a binary category (only two options):

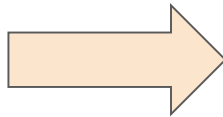
Vertical Direction
UP
DOWN
UP
DOWN



Feature Engineering

- One Hot Encoding (Dummy Variables)
 - Consider a binary category (only two options):

Vertical Direction
UP
DOWN
UP
DOWN



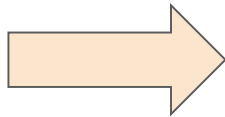
UP	DOWN
1	0
0	1
1	0
0	1



Feature Engineering

- One Hot Encoding (Dummy Variables)
 - The new columns are duplicate information with inverted encoding.

Vertical Direction
UP
DOWN
UP
DOWN



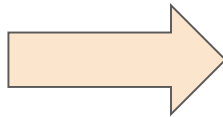
UP	DOWN
1	0
0	1
1	0
0	1



Feature Engineering

- One Hot Encoding (Dummy Variables)
 - Easily fixed by simply dropping last column.

Vertical Direction
UP
DOWN
UP
DOWN



UP
1
0
1
0



Feature Engineering

- One Hot Encoding (Dummy Variables)
 - This can be extended to more than 2 categories:

Country
USA
MEX
CAN
USA



USA	MEX
1	0
0	1
0	0
1	0



Feature Engineering

- One Hot Encoding (Dummy Variables)
 - Pros:
 - No ordering implied.
 - Cons:
 - Potential to create many more feature columns and coefficients.
 - Dummy variable trap consideration.



Feature Engineering

- Throughout this section of the course we'll work on addressing the following issues:
 - Outliers in Data
 - Missing Data
 - Categorical Data
- Not every issue here is strictly “feature engineering”, but could also be called “data cleaning”.



Feature Engineering

- Keep in mind feature engineering in general will always be data and domain dependent.
- There is no one size fits all solution!



Let's get started!



Dealing with Outliers



Outliers

- Often a data set will have a few points that are extreme outliers.
- It's often better to simply remove these few points from the data set in order to have a more generalized model.



Outliers

- Outlier Considerations
 - Definition of an Outlier
 - Range and Limits
 - Percentage of Data
- These are both very domain dependant!



Outliers

- **Outlier Considerations**
 - **Range and Limits**
 - **We need to decide what will constitute an outlier with some methodology:**
 - **InterQuartile Range**
 - **Standard Deviation**
 - **Visualized or Domain Limit Value**



Outliers

- Outlier Considerations
 - Percentage of Data
 - Keep in mind if a large percentage of your data is being labeled as an outlier, then you actually just have a wide distribution, not outliers!
 - Limit outliers to a few percentage points at most.



Outliers

- Outlier Considerations
 - Utilize visualization plots to be able to see and identify outlier points.
 - Keep in mind, this will create caveats for your future model (e.g. Model not suitable for houses priced over \$10 Million)



Outliers

- Keep in mind, there is no 100% correct outlier methodology that will apply to every situation.
- Let's explore the Ames Data Set for outliers!



Dealing with Missing Data

PART ONE: EVALUATING WHAT IS MISSING



Missing Data

- Make sure you've viewed the “Missing Data” lecture in the pandas section **before** continuing with this series of lectures!
- Many concepts and methods referred to here were explained in those lectures.



Missing Data

- Working with the Ames data set, in Part One we will focus on evaluating just how much data is missing.



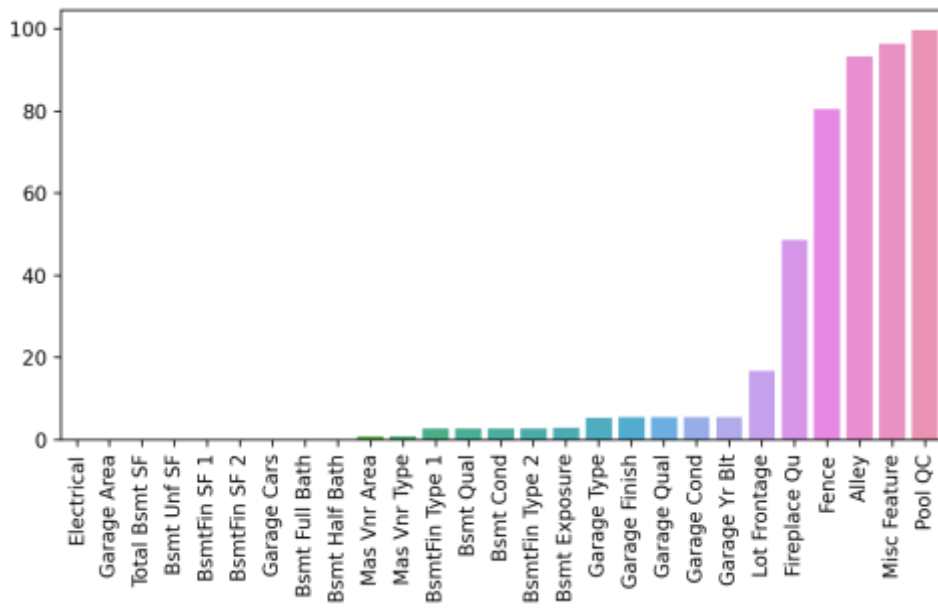
Dealing with Missing Data

PART TWO: FILLING DATA FOR ROWS



Missing Data

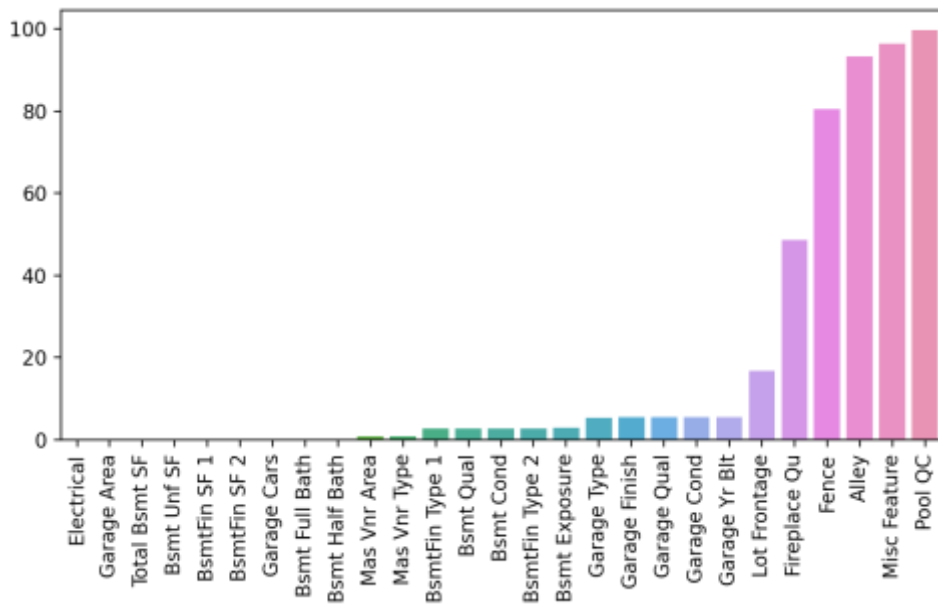
- Recall we just calculated percentage of data missing per feature column:





Missing Data

- Let's first work on considering features that have a very small percent missing.





Missing Data

- In the case of just a few rows missing the feature data, we'll consider either dropping these few rows or filling in with a reasonable assumption based off domain knowledge.
- Let's jump to the notebook to explore our options!



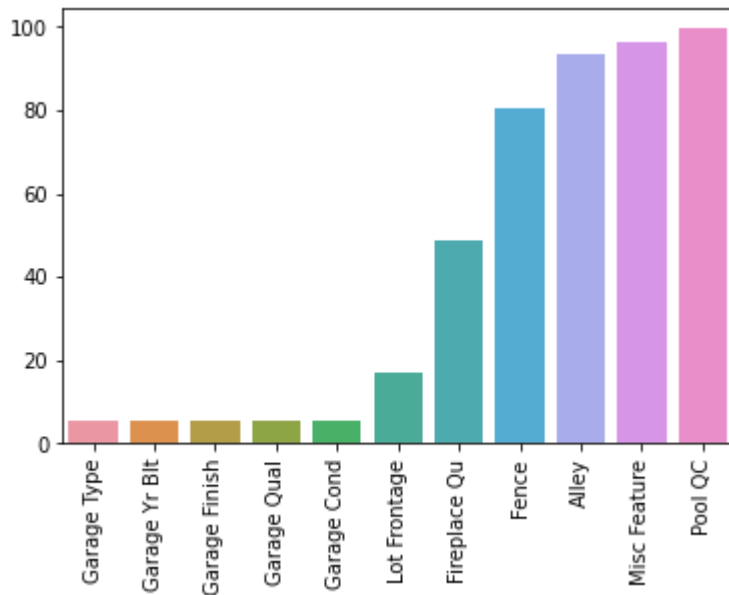
Dealing with Missing Data

PART THREE: FEATURE COLUMNS



Missing Data

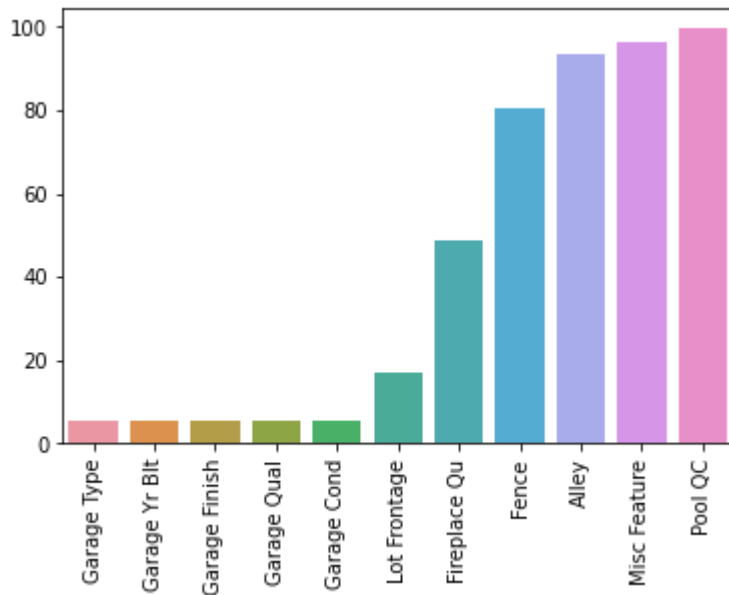
- We are now dealing with missing data that goes beyond our 1% threshold.





Missing Data

- In other words, more than 1% of rows are missing some of these feature values.





Missing Data

- Two main approaches here:
 - Fill in the missing values
 - Drop the feature column
- Let's consider the pros and cons of each approach...



Missing Data

- **Dropping the feature column:**
 - Very simple to do.
 - No longer need to worry about that feature in the future.
 - Potential to lose a feature with possible important signal.
 - Should consider drop feature approach when many rows are NaN.



Missing Data

- Filling in the missing feature data:
 - Potentially changing ground truth in data.
 - Must decide on reasonable estimation to filled value.
 - Must apply transformation to all future data for predictions.



Missing Data

- Filling in the missing feature data:
 - Simplest case:
 - Replace all NaN values with a reasonable assumption (e.g. zero if assumed NaN implied zero)
 - Harder cases:
 - Must use statistical methods based on other columns to fill in NaN



Missing Data

- Filling in the missing feature data:
 - Statistical Estimation:
 - Dataset about people with some age data missing.
 - Could use current career/education status to fill in data (e.g. people currently in college fill in with 20 yrs)



Missing Data

- **Let's explore both approaches!**
 - *Important note!*
 - *Realistically on the Ames data set, many NaN values are probably actually correctly “zero”. But we want to show the methodology for multiple approaches!*



Dealing with Categorical Data



Categorical Data

- We're going to jump straight to the transformation of the data, but make sure to have watched the section introduction lecture in full for a detailed discussion on dummy variables and one hot encoding!