Machine Learning

06048203

Feature Engineering and Data Preparation

Feature Engineering

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

Country
USA
MEX
CAN
USA

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
    - 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 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)
  - 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)
  - Consider a binary category (only two options):

Vertical Direction
UP
DOWN
UP
DOWN

Feature Engineering

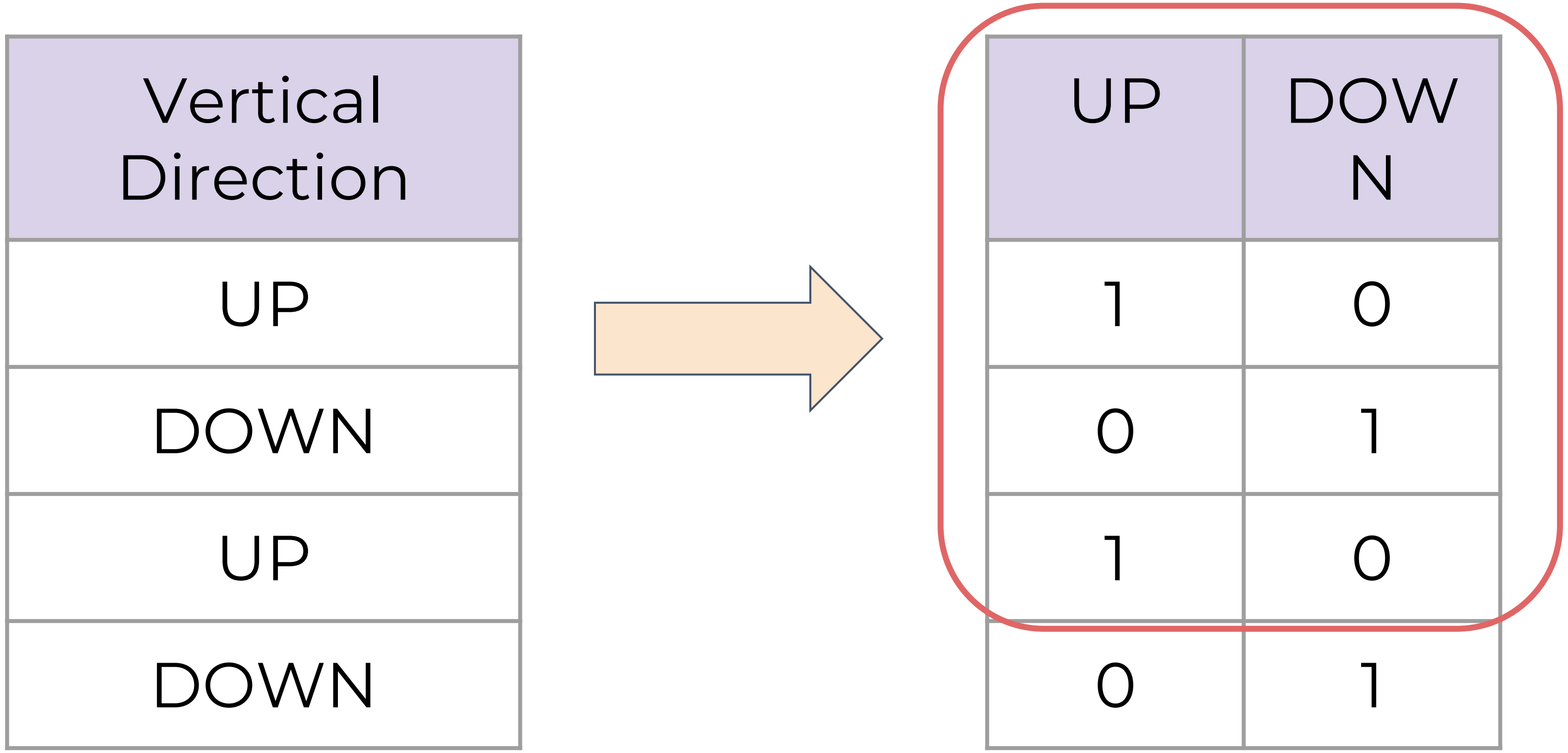
- One Hot Encoding (Dummy Variables)
  - Consider a binary category (only two options):

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.
        - Not easy to add new categories.

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 a 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

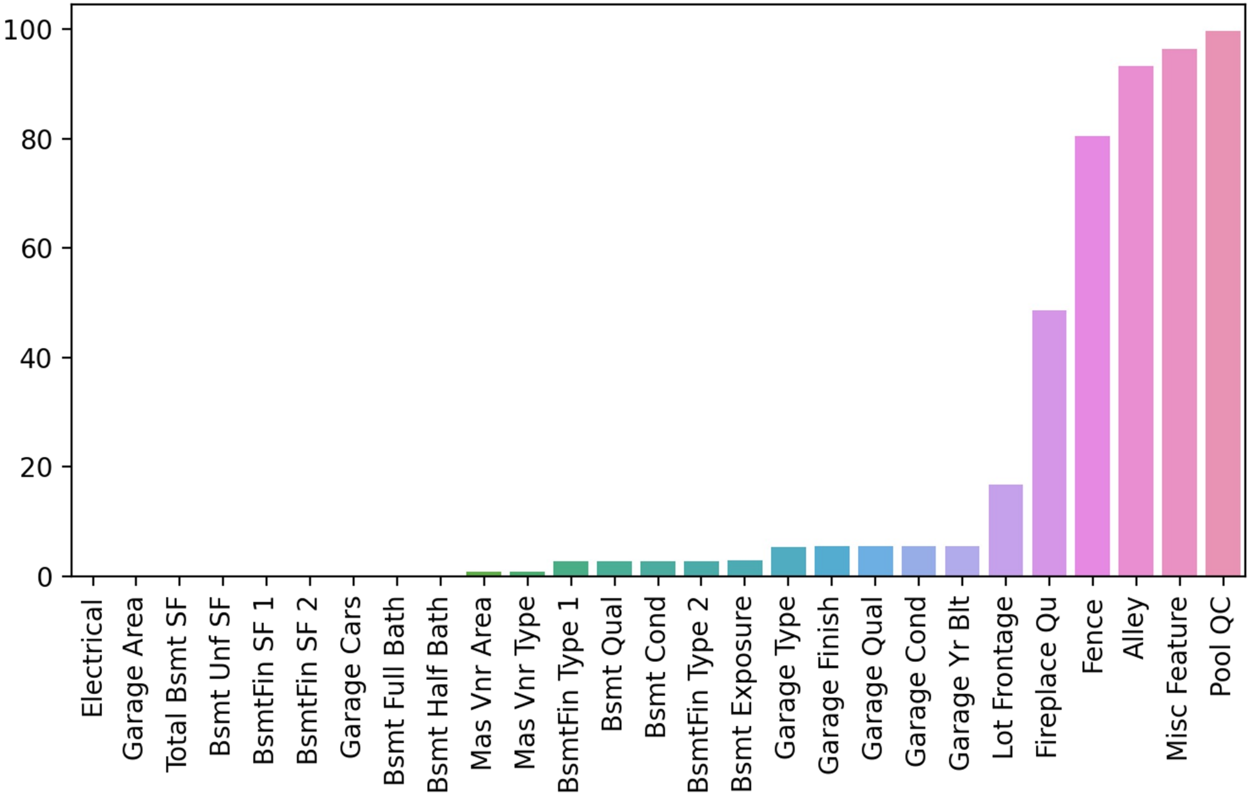
- Working with the Ames data set, in Part One we will focus on evaluating just how much data is missing.

Dealing with Missing Data

PART TWO: FILLING DATA FOR ROWS

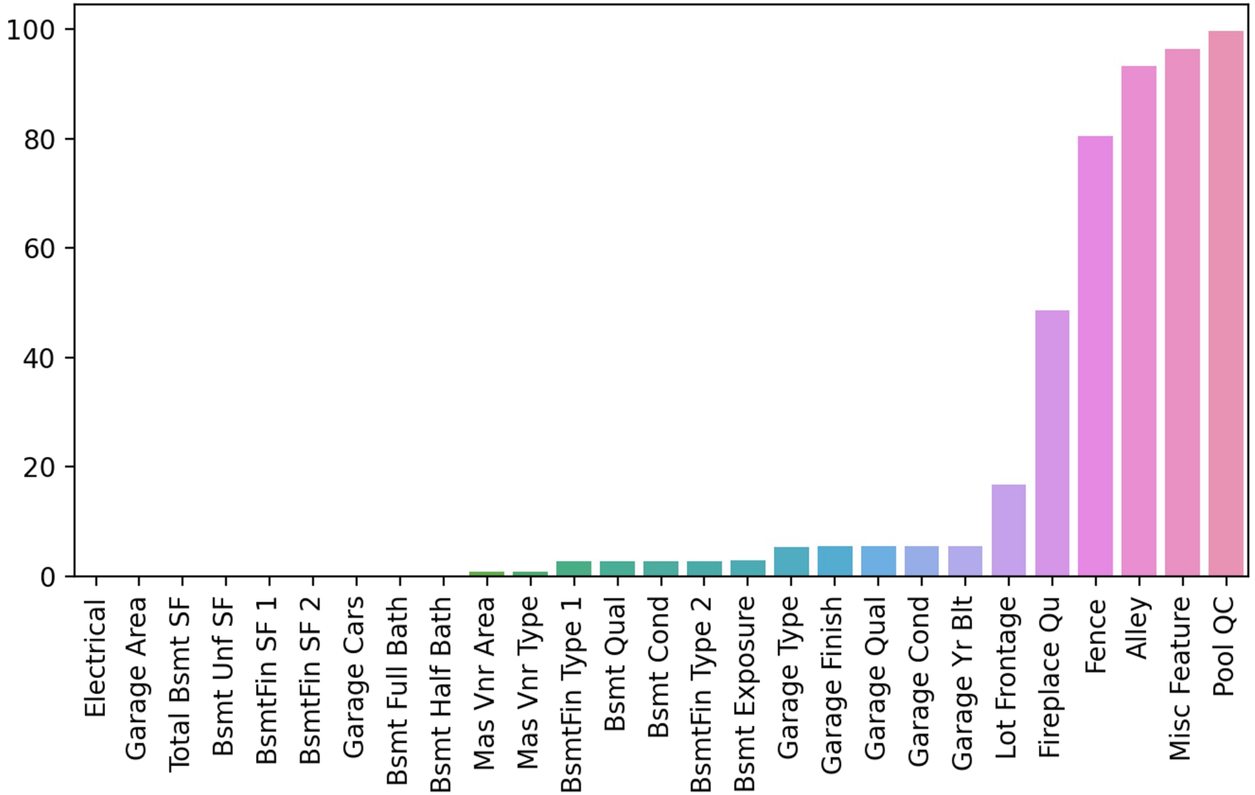
Missing Data

- 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

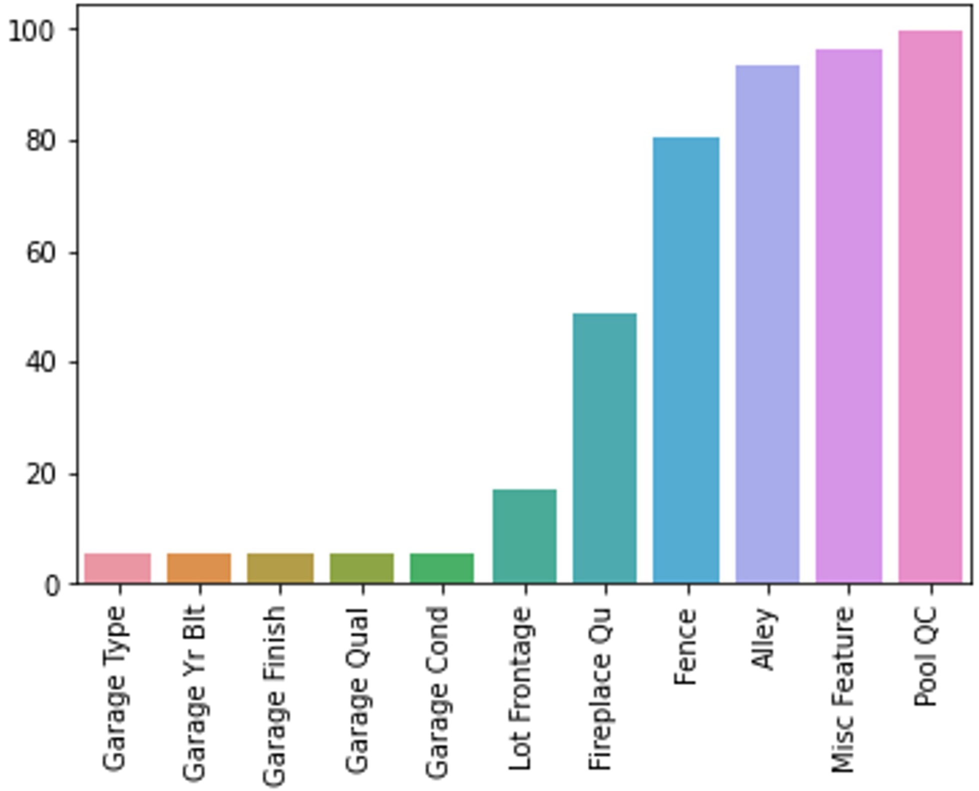
- In the case of just a few rows missing the feature data, we’ll consider either dropping these few rows or filling in with a reasonable assumption based off domain knowledge.
- Let’s jump to the notebook to explore our options!

Dealing with Missing Data

PART THREE: FEATURE COLUMNS

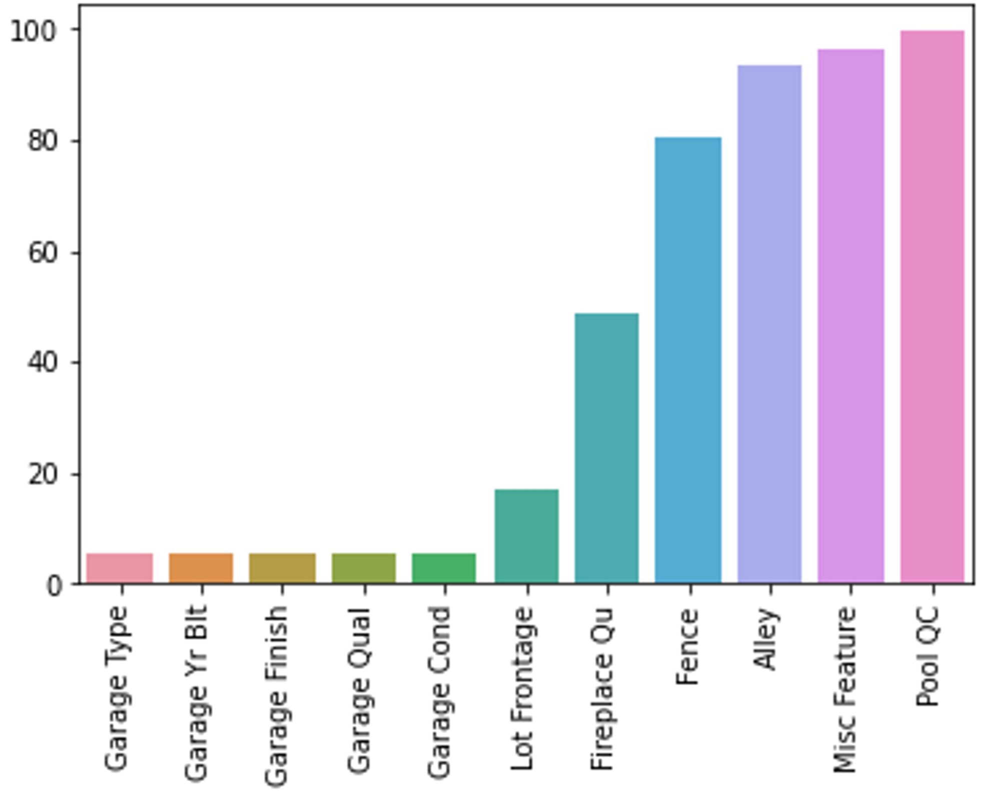
Missing Data

- 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 values.

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!