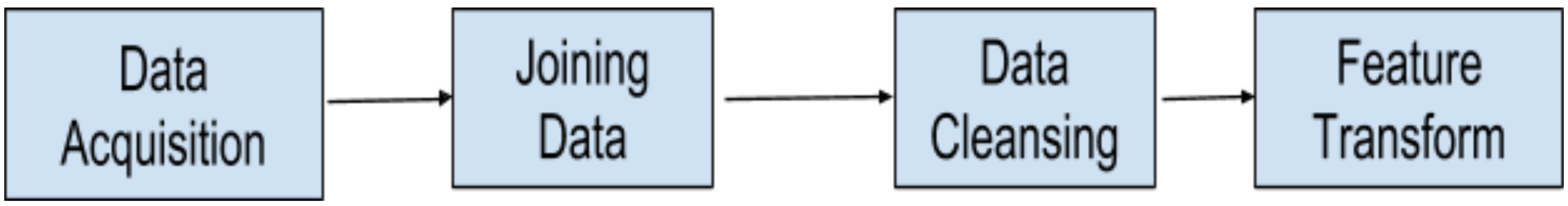
Data Wrangling

Data wrangling is the process of cleaning and unifying messy and complex data sets for easy access and analysis.

Goals of Data Wrangling are:

- Reveal a “deeper intelligence” within your data, by gathering data from multiple sources
- Provide accurate, actionable data in the hands of business analysts in a timely matter
- Reduce the time spent collecting and organizing unruly data before it can be utilized
- Enable data scientists and analysts to focus on the analysis of data, rather than the wrangling
- Drive better decision-making skills by senior leaders in an organization

Key steps in Data Wrangling



These data are readily and publicly available at https://www.kaggle.com/c/home-credit-default-risk/data and appear as below:

SK_ID_CURR	TARGET	NAME_CONT	CODE_GEND	FLAG_OWN_	FLAG_OWN_	CNT_CHILDR	AMT_INCOM	AMT_CREDIT	AMT_ANNUI	AMT_GOODS	NAME_TYPE_	NAME_INCO	NAME_EDUC	NAME_FAMI	NAME_HOUS	REGION_POI	DAYS_BIRTH	DAYS_EM
100002	1	Cash loans	M	N	Y	0	202500	406597.5	24700.5	351000	Unaccompar	Working	Secondary /	Single / not r	House / apar	0.018801	-9461	-6
100003	0	Cash loans	F	N	N	0	270000	1293502.5	35698.5	1129500	Family	State servant	Higher educa	Married	House / apar	0.003541	-16765	-11
100004	0	Revolving loa	M	Y	Y	0	67500	135000	6750	135000	Unaccompar	Working	Secondary /	Single / not r	House / apar	0.010032	-19046	-2
100006	0	Cash loans	F	N	Y	0	135000	312682.5	29686.5	297000	Unaccompar	Working	Secondary /	Civil marriag	House / apar	0.008019	-19005	-30
100007	0	Cash loans	M	N	Y	0	121500	513000	21865.5	513000	Unaccompar	Working	Secondary /	Single / not r	House / apar	0.028663	-19932	-30
100008	0	Cash loans	M	N	Y	0	99000	490495.5	27517.5	454500	Spouse, part	State servant	Secondary /	Married	House / apar	0.035792	-16941	-15
100009	0	Cash loans	F	Y	Y	1	171000	1560726	41301	1395000	Unaccompar	Commercial	Higher educa	Married	House / apar	0.035792	-13778	-31
100010	0	Cash loans	M	Y	Y	0	360000	1530000	42075	1530000	Unaccompar	State servant	Higher educa	Married	House / apar	0.003122	-18850	-4
100011	0	Cash loans	F	N	Y	0	112500	1019610	33826.5	913500	Children	Pensioner	Secondary /	Married	House / apar	0.018634	-20099	3652

The datasets required extensive data wrangling for it involved not only fundamental steps of data preparation but also feature engineering and data imputation to be run during Machine Learning:

1. Extracting Data
2. Identifying Target Dataset among Multiple Data Sources

3. Identifying Missing Data
4. Identifying Data Types of the Feature Set into Non-Categorical and Categorical
5. Casting Data Types per Need
6. Feature Engineering (Date timestamp, One Hot Encoding)
7. Baseline Machine Learning Modeling

Here is the detailed codebook showing above steps:

https://github.com/rashi-n/Machine-Learning-Projects/blob/master/Capstone%20Projects/Capstone%20II%20Project/Data%20Wrangling.ipynb

Following the highlights from the codebook:

I. Among multiple datasets for Credit Accounts and Transactions, 'Application_train' and 'Application_Test' datasets were deduced to import as they seemed to carry most of the features that may be significant in analysis & predictions of the project objective. The main training and testing data with information about each loan application at Home Credit. Every loan has its own row and is identified by the feature SK_ID_CURR. The training application data comes with the TARGET indicating 0: the loan was repaid or 1: the loan was not repaid.:

```
In [2]: #Importing the dataset
        df_train = pd.read_csv('application_train.csv')
        df_test=pd.read_csv('application_test.csv')

In [3]: #Shape of dataset
        df_train.shape

Out[3]: (307511, 122)
```

II. Dataset carries nearly 307K records with 121 features and one 'TARGET' variable to infer predictions on each transaction.

III. There were 67 columns that had missing values

```
Your selected dataframe has 122 columns.
There are 67 columns that have missing values.
```

	Missing Values	% of Total Values
COMMONAREA_MEDI	214865	69.9
COMMONAREA_AVG	214865	69.9
COMMONAREA_MODE	214865	69.9
NONLIVINGAPARTMENTS_MEDI	213514	69.4
NONLIVINGAPARTMENTS_MODE	213514	69.4
NONLIVINGAPARTMENTS_AVG	213514	69.4
FONDKAPREMONT_MODE	210295	68.4
LIVINGAPARTMENTS_MODE	210199	68.4
LIVINGAPARTMENTS_MEDI	210199	68.4
LIVINGAPARTMENTS_AVG	210199	68.4
FLOORSMIN_MODE	208642	67.8
FLOORSMIN_MEDI	208642	67.8
FLOORSMIN_AVG	208642	67.8
YEARS_BUILD_MODE	204488	66.5
YEARS_BUILD_MEDI	204488	66.5
YEARS_BUILD_AVG	204488	66.5
OWN_CAR_AGE	202929	66.0
LANDAREA_AVG	182590	59.4
LANDAREA_MEDI	182590	59.4
LANDAREA_MODE	182590	59.4

IV. Of the 122 features, 106 were non-categorical and 16 were categorical:

```
# Number of each type of column
df_train.dtypes.value_counts()
```

```
float64    65
int64      41
object     16
dtype: int64
```

V. **Feature Engineering**

The features were appropriately cast into right data types and categorical features were Label Encoded and One Hot Encoded. The categorical variables with less number of classes (<=2) may be label encoded while remaining I may use One Hot encoding technique. The reason why we have to feature engineer Categorical variables is because many Machine Learning Model do not perform well with Categorical variables since categorical variable may have too many levels and pulls down performance level of the model. Also it is not necessary that all the levels always occur in the records, only few may occur and make any impact on model fit.

VI. **Aligning Training and Testing Data**

There need to be the same features (columns) in both the training and testing data. After feature engineering categorical variables in the dataset now we have more columns in the traning (primary) dataset and test dataset since does not have target label so at this point I align the feature set in the two datasets before we take further steps on baselining model.

('Training Features shape: ', (307511, 240))

('Testing Features shape: ', (48744, 239))

The training and testing datasets now have the same features which is required for machine learning. The number of features has grown significantly due to one-hot encoding.

VII. **Baseline Machine Learning Modeling**

With 70 % data missing in some of the 67 columns (total 122 features) it is important to understand how to deal with missing data. As we learn more data science/statistics, we'll learn about data imputation. Here, we'll learn to find missing data points and then we'll drop those points from the dataset so as not to affect our analysis with bias: an important part of data wrangling and data cleaning. We'll try to find which columns in 'df_train.csv' contain missing values and drop those missing values so you'll have tidy data.

Missing Values Strategy # 1 - Identify Features with Missing Values -> Replace with NaN -> Remove all Features with Missing Value -> Assess Model using Logistic Regression

Missing Values Strategy # 2 - Identify Features with Missing Values -> Replace with NaN -> Impute all Features with Missing Value -> Assess Model using Logistic Regression

Followed both the approaches and created Logistic REgression model with following accuracies respectively:

Accuracy of logistic regression classifier on test set: 0.93 with Strategy #1

Accuracy of logistic regression classifier on test set: 0.92 with Strategy#2

```
y_pred = logreg.predict(X_test)
print('Accuracy of logistic regression classifier on test set: {:.2f}'.format(logreg.score(X_test, y_test)))
```

```
Accuracy of logistic regression classifier on test set: 0.92
```

Now our baseline model is ready to start Exploratory & Inferential Data Statistics.

Outlier Analysis

Outlier analysis is done to ensure there is no anomaly in the data that may influence model prediction adversely. So I did outlier analysis on 'Birth_days', 'Days_Employed' to ensure data is within possible range.

```
(df_train['DAYS_BIRTH']/365.0).describe()
```

```
count    307511.000000
mean         43.936973
std          11.956133
min          20.517808
25%          34.008219
50%          43.150685
75%          53.923288
max          69.120548
Name: DAYS_BIRTH, dtype: float64
```

There is no outlier by the AGE either the low or high end. Same we can confirm for Days of Employment.