Machine Learning Engineer Nanodegree

Capstone Project

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I. Definition

Project Overview

For my capstone project, I have chosen to work on a competition posted on kaggle.com - Avito Demand Prediction challenge (https://www.kaggle.com/c/avito-demand-prediction)

Domain Background

Avito Demand Prediction competition wants to predict the likelihood/probability that an advertisement that is posted on their social advertisement website sells the item that is being advertised. Based on various details of an advertisement posted, the company would like to give feedback to the seller on the likelihood that the ad will sell. This will help set expectations of the seller, so they are not frustrated with the website if the item does not sell. It will also give the seller an opportunity to review the posting, to help improve the likelihood of the item being sold (e.g. may be include a detailed description, better picture, etc)

I am interested in solving this problem because of the nature of the inputs that need to be analyzed - tabular data, textual data and image data to predict the likelihood of selling. Typically, in the homeworks/assignments that I have worked on so far, the data was of single type (either tabular data or textual data or image data). When I saw that this problem had a mix of inputs, it piqued my interest in how I would address this issue and how I would set up this problem. Also at a personal level, in the past, there were many of my ads (that I posted on various social advertisement websites) that never sold. I would have definitely welcomed any feedback on the likelihood of the ad selling from any one of these websites.

Problem Statement

Given an advertisement, i.e, information on item to be sold, such as description, price, image, etc, a '***deal probability***' should be predicted by the system. Deal probability is a continuous variable ranging between 0.0 to 1.0. Higher probability will indicate greater likelihood that the advertisement will sell and lower probability will indicate less likelihood that the advertisement will sell the item.

Datasets and Inputs

The competition data has been provided by Avito (https://www.kaggle.com/c/avito-demand-prediction/data). Of importance for my capstone project were:

- train.csv - Training data.
    - `item_id` - Ad id.
    - `user_id` - User id.
    - `region` - Ad region.
    - `city` - Ad city.
    - `parent_category_name` - Top level ad category as classified by Avito's ad model.
    - `category_name` - Fine grain ad category as classified by Avito's ad model.
    - `param_1` - Optional parameter from Avito's ad model.
    - `param_2` - Optional parameter from Avito's ad model.
    - `param_3` - Optional parameter from Avito's ad model.
    - `title` - Ad title.
    - `description` - Ad description.
    - `price` - Ad price.
    - `item_seq_number` - Ad sequential number for user.
    - `activation_date`- Date ad was placed.
    - `user_type` - User type.
    - `image` - Id code of image. Ties to a jpg file in train_jpg. Not every ad has an image.
    - `image_top_1` - Avito's classification code for the image.
    - `deal_probability` - The target variable. This is the likelihood that an ad actually sold something. It's not possible to verify every transaction with certainty, so this column's value can be any float from zero to one.
- train_jpg.zip - Images from the ads in train.csv.
- test.csv - Test data used by Kaggle to generate the prediction score
    - The columns are identical to train.csv except the deal_probabillity column.

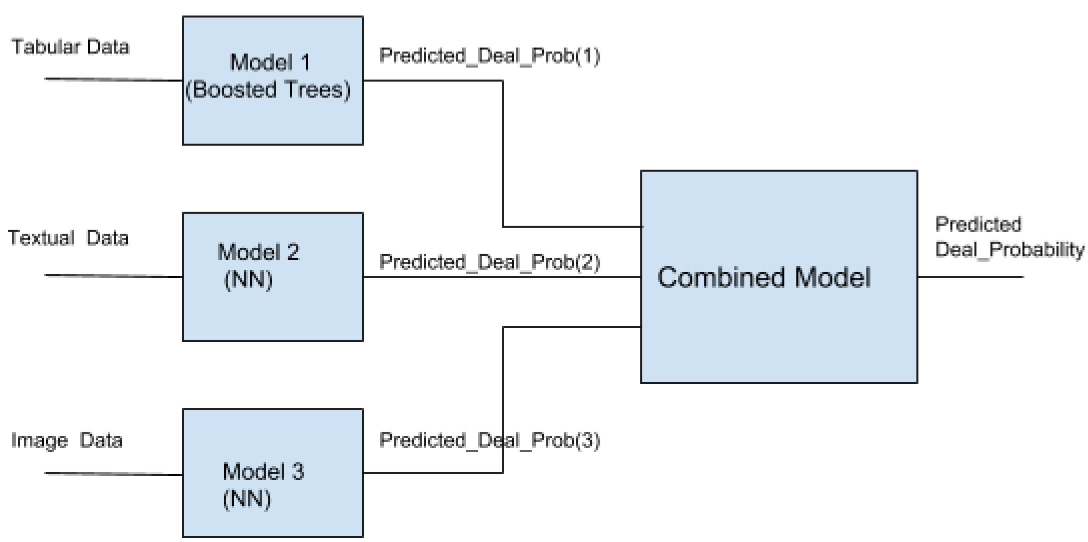
- test_jpg.zip - Images from the ads in test.csv

train.csv has 1.5 Million rows of data. Each row indicates an ad item that was published by the user on Avito website. Not all rows have description and not all rows have an associated image (i.e. the image of the item the user is trying to sell). The size of the file is 908MB. The size of train_jpg.zip is ~40GB.

As the kaggle competitions is active, to measure the performance of my models on the test data, I have made submissions to Kaggle to generate the performance metric on the models.

Solution Statement

As the data set is labeled and target variable is continuous, I used supervised learning algorithms to design the model (e.g. Boosted Tree Regression and Neural Net Regression techniques). Also, as the input is primarily of three types of data (tabular data, textual data and images), I built three different models for each type of input and then used another regression model to combine the outputs of the three models to get the final prediction.



For Model 1, the input (X_train) was mostly all the columns found in train.csv and the label (y_train) was the corresponding 'deal_probability' value. For Model 2, the X_train was the vector representation of the 'description' column and y_train was the corresponding ‘deal_probability’ from train.csv. For Model 3, X_train was the matrix representation of the image and the corresponding ‘deal_probability’ from train.csv. For all three models, the output was the predicted deal_probability value given their respective X input.

The next step in the model building process was to build the combined model that takes the outputs of these three models (individual deal_probability values) and combine them to predict the final value for the target variable.

Metrics

As the competition is being evaluated on the Root Mean Squared Error (RMSE) score, I intend to use this metric for evaluating my models.

RMSE is defined as

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(target_{i\ actual} - target_{i\ predicted})2}$$

Where n = the number of testing data points, target_actual = actual target variable value (between 0.0 and 1.0), target_predicted = predicted target variable value (between 0.0 and 1.0). The goal would be to build a model that has a value of RMSE close to 0.0

Given the nature of the target variable (continuous), I think RMSE is a good evaluation metric.

II. Analysis

Data Exploration and Visualization:

In this phase, my primary goal was to understand how various attributes (in train.csv) relate to one another and their correlation to the target variable. I sliced and diced the data in several different ways to gain familiarity with the data and see if there were any correlations among the various columns in train.csv. I started with simple bar charts to get the distribution of the data by individual columns and then used scatter plots to plot combination of columns to see if there are any trends among various columns. (E.g, - distribution of deal_probability by parent category, etc). I have included a few graphs of interest, but the python notebook has more details on the ways I grouped the data, statistics on individual groups, etc.

Below is the output from the dataframe describe on the train_data and test_data. I am ignoring item_seq_number (as this is enumerated value of ad sequential number and image_top_id as this is categorical value and not numerical)

Screenshot of train.describe()

	price	item_seq_number	image_top_1	deal_probability
count	1.418062e+06	1.503424e+06	1.390836e+06	1.503424e+06
mean	3.167081e+05	7.436740e+02	1.241932e+03	1.391306e-01
std	6.689154e+07	5.572522e+03	9.704641e+02	2.600785e-01
min	0.000000e+00	1.000000e+00	0.000000e+00	0.000000e+00
25%	5.000000e+02	9.000000e+00	4.250000e+02	0.000000e+00
50%	1.300000e+03	2.900000e+01	1.057000e+03	0.000000e+00
75%	7.000000e+03	8.800000e+01	2.217000e+03	1.508700e-01
max	7.950101e+10	2.044290e+05	3.066000e+03	1.000000e+00

Screenshot of train.describe()

	price	item_seq_number	image_top_1
count	4.778530e+05	508438.000000	465829.000000
mean	2.798189e+05	825.132150	1297.959228
std	5.364218e+06	5646.868618	961.065300
min	0.000000e+00	1.000000	0.000000
25%	5.000000e+02	8.000000	467.000000
50%	1.500000e+03	30.000000	1132.000000
75%	8.600000e+03	94.000000	2218.000000
max	3.000060e+09	205064.000000	3066.000000

From the summarized statistics on price column, it can be seen that there is wide range of values. This intuitively makes sense, because, if you look at the categories of items being sold, they include everything from baby toys to selling real-estate. To address this, I applied log transformation to the price column. Also, as the rest of the columns are all categorical, please refer to the section on **Handling high cardinal categorical values** in the document below.

From the summarized statistics on deal_probability, it can be seen the average deal_probability is very low (**1.391306e-01**). I wanted to better understand the deal_probability distribution by parent_category, especially to see if there is a skew towards some categories compared to other.

	deal_probability							
	count	mean	std	min	25%	50%	75%	max
parent_category_name_en								
Animals	52470.0	0.235957	0.286774	0.0	0.00000	0.10994	0.38305	0.78503
Consumer electronics	173008.0	0.175421	0.279319	0.0	0.00000	0.00000	0.24873	0.76786
For business	18075.0	0.111026	0.216779	0.0	0.00000	0.00000	0.11742	0.78912
For the home and garden	178823.0	0.179633	0.307092	0.0	0.00000	0.00000	0.22296	0.86521
Hobbies & leisure	86011.0	0.123703	0.260213	0.0	0.00000	0.00000	0.09587	0.82668
Personal belongings	697623.0	0.075876	0.209260	0.0	0.00000	0.00000	0.00000	0.80323
Real estate	153190.0	0.142051	0.192078	0.0	0.00000	0.07438	0.18992	1.00000
Services	64385.0	0.403123	0.346907	0.0	0.14286	0.33333	0.60000	1.00000
Transport	79839.0	0.263336	0.292592	0.0	0.00000	0.12974	0.48305	0.74043

'**Services**' parent_category has the highest average deal_probability. Its interesting to observer that '**Personal belongings**' section has the lowest average deal_probability, but has the highest number of ads that belong to this category (highest count - 697623). I wanted to drill down on this to see the distribution of deal_probabilities among the sub-categories of 'Personal belongings'

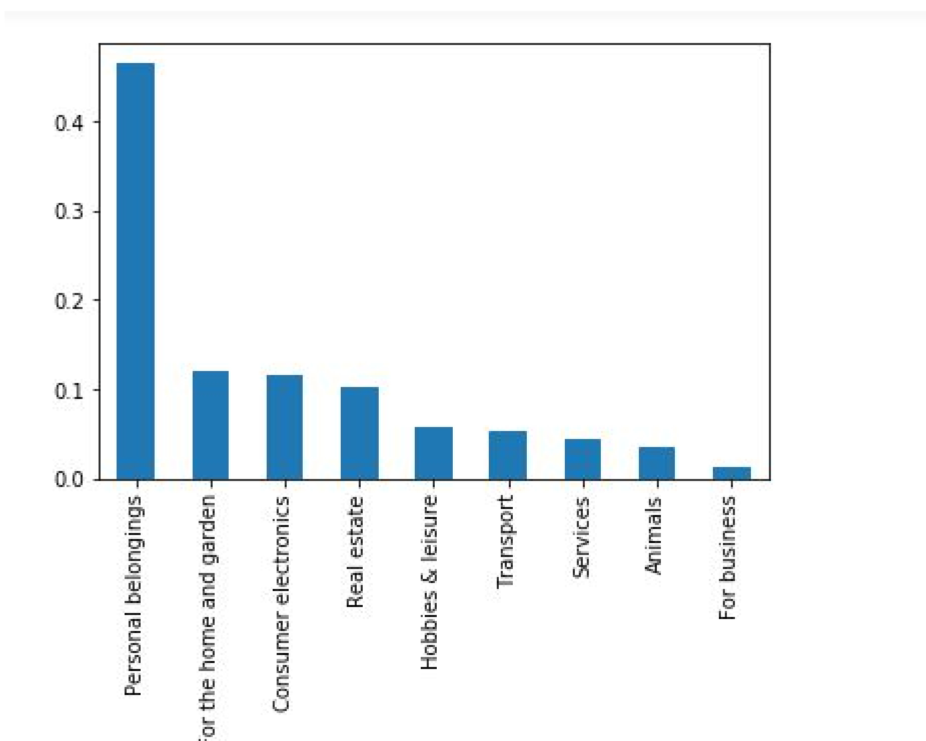
		price	deal_probability
parent_category_name_en	**category_name_en**		

Personal belongings	**Children's clothing and shoes**	9.787546e+03	0.060834
	Children's products and toys	4.129398e+03	0.198445
	Clothing, shoes, accessories	8.243247e+03	0.046447
	Health and beauty	4.512370e+03	0.092382
	Watches and jewelry	1.335892e+04	0.055316

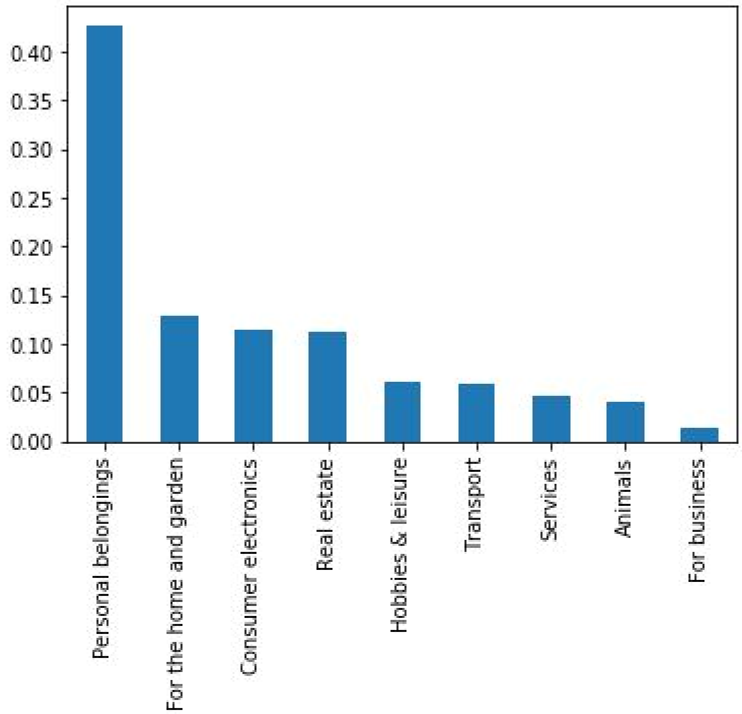
Along with understanding the data, I was also checking if the train data is a balanced set and represents what is found in test data well. For example, below shows the distribution of the ads by ‘parent_category_name’ column in train data and test data to see if the distribution is similar or not. From the graph, it can be seen that the train data distribution is a good representation of what is seen in test data as well.

- parent_category_name - Top level ad category as classified by Avito's ad model.

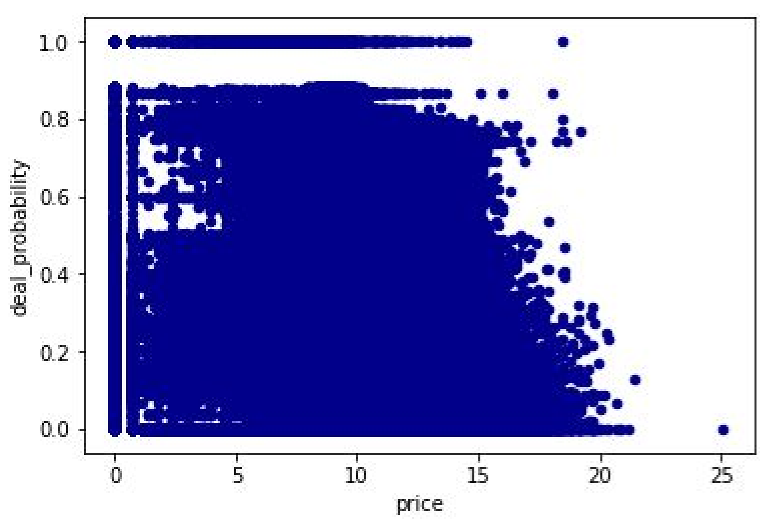
Normalized distribution of ads in train data by parent_category



Normalized distribution of ads in test data by parent category



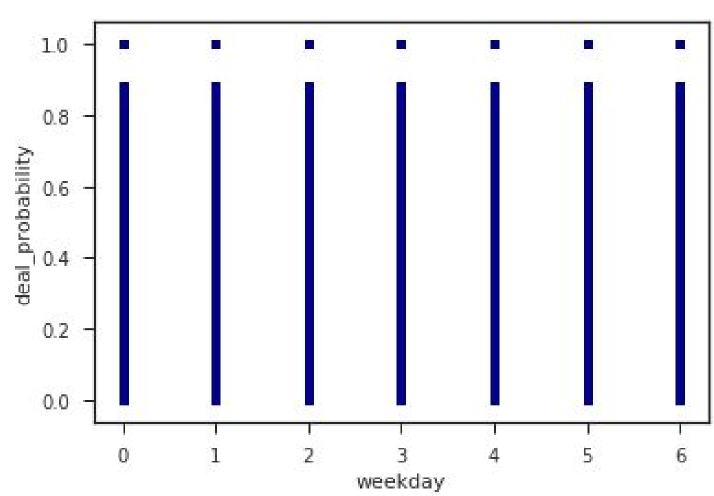
- price - Ad price. Scatter plot of the target variable (deal_probability and price). Wanted to see if there were any patterns, such as low priced items having higher deal_probability, etc. If there were, I was going to further explore or isolate the data to better understand the dynamics of these variables. However, the image below shows a very uniform distribution of data. (Note, price on this graph has been log scaled to address the wide range of data)



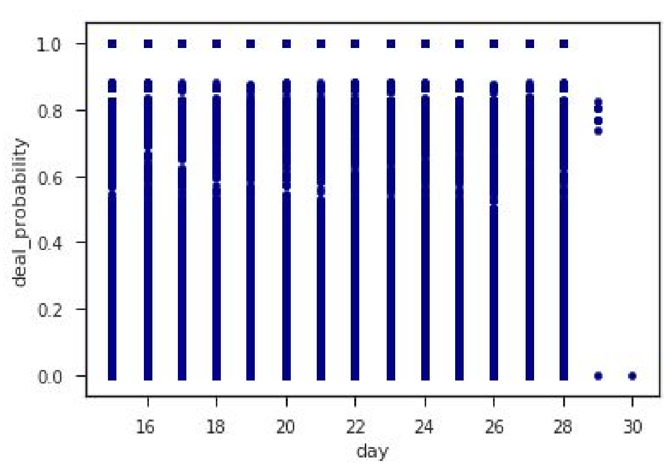
Feature Engineering

- activation_date- Date ad was placed. Broke the data into three subcomponents - day, month and year of the date. Wanted to see if there were any correlations of deal_probability based on when the ad was placed. For example, did the ads that were activated on weekend have a higher deal_probability, or ads placed earlier on in the month have a higher deal_probability. From the visual below, it was clear that no such patterns existed in the data.

Plot showing weekday vs. deal_probability of train data



Plot showing day vs. deal_probability of train data



Take away from this was that the training data come mostly from the last two weeks of the month.

I have also used pairwise plot to visualize the feature data in train.csv. Did not include it in the report due to image resolution limitation (it was looking like an eye-chart). Please refer to the output in the ipython notebook. Briefly, used the encoded categorical values when creating the pairwise grid (please see below for the details on encoding of categorical values). The grid confirmed some of the observations I had seen earlier on - train data was mostly covering the last two weeks of the month, absence of any ‘apparent’ correlations among the columns, etc. When I see data like this (that doesn’t seem to have too many visible patterns), I appreciate the ML algorithms/techniques that learn function(s) over this data to uncover the relationship(s) that can predict the dependent variable.

Algorithms and Techniques

When considering algorithms for Model 1, I was leaning towards using an algorithm that uses decision trees, primarily due to the ease of understanding how the various features are used to predict the target variable and how well the trees handle missing and categorical values. After some initial experimentation with a few variations of tree based models (DecisionTreeRegressor, eXtreme Gradient Boosted trees),I decided to use XGB (https://xgboost.readthedocs.io/en/latest/). I was mostly motivated to use this due to the low RMSE score observed on my initial training data, as well as seeing that numerous Kaggle winning competitions used XGB model.

XGB model uses iterative tree ensemble techniques. Each iteration (a new tree) tries to minimize the error observed in the previous iteration. The final prediction is sum of predictions of multiple trees. Below is the mathematical form of the model (https://xgboost.readthedocs.io/en/latest/model.html)

$$\hat{y_i} = \sum_{k=1}^{K} f_k(x_i), f_k \in \mathcal{F}$$

where K is the number of trees, f is a function in the functional space $\mathcal{F}$, and $\mathcal{F}$ is the set of all possible CARTs. Therefore our objective to optimize can be written as

$$\text{obj}(\theta) = \sum_{i}^{n} l(y_i, \hat{y_i}) + \sum_{k=1}^{K} \Omega(f_k)$$

One of the primary differences between XGB and Random Forest is how the model is built. Random Forest builds the trees simultaneously, where as XGB builds the trees linearly, each tree starting with the error from the prior tree.

Some of the key parameters to control over-fitting are:

- max_depth - maximum depth of the tree. This controls the complexity of the tree
- min_child_weight - indicator when the tree should stop partitioning the leaves
- gamma - minimum loss reduction required to make a further split on the leaf node of the tree.
- subsample - ratio of the samples from the training data
- Colsample_bytree - ratio of samples from individual columns of the training data

For Model 2, I used a two layer Neural Net to process the description data. My primary motivation came from the literature I read about for sentiment analysis using NN . In the sentiment analysis case, the textual data is converted to multi dimensional input space (via tf-idf or word2vec) and a NN is trained to identify if the sentiment is positive or negative. In my case, I used TF_IDF and SVD to convert the description column data into multidimensional data, which is used as input to my two layer NN to predict the 'deal_probability'

Typically, a NN will have an input layer, one or more hidden layers and an output layer. Each layer in the NN will have multiple nodes. Each node represents a linear combination of weights and inputs that are applied together to generate a value that will feed into the next layer, that in turn helps predict the output. The weights are adjusted based on backpropagation of errors method. There are multiple parameters that are critical in adjusting the weights of the NN (https://keras.io/models/sequential/). Below are a few, that I have focused on to complete this project.

- Number of Epochs - an Epoch is an iteration over entire training data set. This is critical, because if you did not train the NN over sufficient number of epochs, the weights may not have converged to best predict the target variable
- Batch_size - its the number of samples used per gradient update of the network.

For Model 3, I used a CNN to train and predict the target variable. I found that this was very similar to the Dog Breeder Classifier project, with the exception that in this competition, the target variable is continuous and not discrete. I changed the last layer of CNN to have a sigmoid function that would give the output value between 0 and 1.

A CNN is a type of NN that is generally used for working with image data. Apart from the input and output layer, CNN has convolutional layers, pooling layers and fully connected layers. They can take a matrix as an input. Again, as NN, CNNs have many parameters that can be tuned to better predict the target variable. Similar to NN, I have focused on the Number of Epochs and Batch_size parameters when training the CNN.

Benchmark

As this an active Kaggle competition, there hasn't been a published model yet. So, as a benchmark model, I used a simple linear regression model based only on tabular data in train.csv (i.e, excluded description and image data). I systematically compared the RMSE score of benchmark model with that of the various combined models. My hypothesis is that the combined model, as they are using additional forms of data/information, should perform better than the benchmark solution.

III. Methodology

Data Preprocessing

- Below are the steps I followed to prepare the data in train.csv
- For Model 1:
    - Checked for missing values - calculated the percent missing. Below is a snapshot of the output from the function.

```
Missing Train data ********************************
param_1 has 4.09571750883317 of data missing
param_2 has 43.536753437486695 of data missing
param_3 has 57.3733690562343 of data missing
price has 5.677839385296497 of data missing
image_top_1 has 7.48877229577285 of data missing
Missing Test data ********************************
param_1 has 4.505957461873424 of data missing
param_2 has 45.87166970210724 of data missing
param_3 has 60.24943060904181 of data missing
price has 6.015482713723207 of data missing
image_top_1 has 8.380372828152105 of data missing
```

    - Dropped 'param_3' column as it had more than 57% and 60% missing data in train and test data. (As a future improvement, I may go back to this and fill in a 'placeholder' value for the missing data and run thru the various models to see if it improves the RMSE score)

- Classified the number of columns as categorical, ordinal, continuous, binary
    - Apart from price, all the columns were categorical columns. Below is the count of cardinal values by columns

```
region :28
city :1733
parent_category_name :9
category_name :47
param_1 :372
param_2 :272
image_top_1 :3063
user_type :3
weekday :7
```

    - **Handling high cardinal categorical values**: As seen from the output above, most of the columns have high cardinality (e.g., image_top has about 3000 cardinality). One-hot encoding is not the appropriate technique, as this will increase the dimensionality of the data rapidly. During my exploration process, I label-encoded the various categories. This does address the dimensionality increase issue, but inherently imposes an ordinal structure and depending on the model I choose, may lead to incorrect results. I searched for other techniques of handling high cardinal categorical columns and found the paper *'A Preprocessing Scheme for High-Cardinality Categorical Attributes in Classification and Prediction Problems' by Daniele Micci-Barreca* (https://kaggle2.blob.core.windows.net/forum-message-attachments/225952/7441/high%20cardinality%20categoricals.pdf). The technique converts categorical column values into continuous range of values using target statistics. I applied this technique to convert all the categorical columns found in train.csv and test.csv

- For Model 2:
  - Model 2 only used the 'description' column of train.csv as input data. 7.73% of the data was missing description information. Used a placeholder value for the missing data.

    - Used TF-IDF and Truncated SVD from sklearn to get the top 125 svd components of description column data.
- For Model 3:
    - Model 3 used the images data. I used the Keras image processing package to read them and convert them into 3d array representations.

Implementation and Refinement

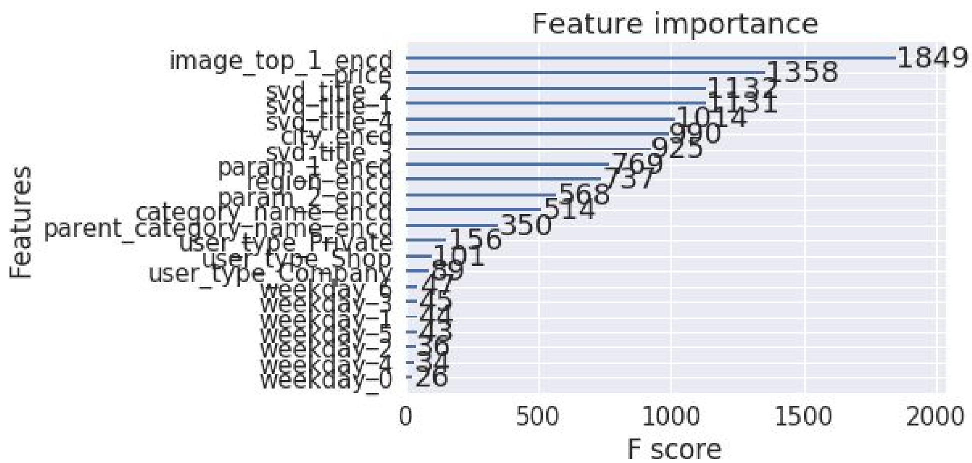
Once the data was pre-processed and ready, the code for train, validation and testing were relatively straight forward. Most of the time was spent tuning the various model parameters.

Model 1 - tuning XGB model:

XGB model comes with many parameters that can be tuned to deal with bias-variance tradeoff. Off importance for controlling overfitting are ‘max_depth’, ‘min_child_weight’,’gamma’, ‘subsample’ and ‘colsample_bytree’. (http://xgboost.readthedocs.io/en/latest/parameter.html)

With an initial set of booster parameter values (*'eta': 0.3, 'subsample': 1.0, 'colsample_bytree': 0.8, 'objective': 'binary:logistic', 'max_depth':5, 'min_child_weight':3*), performed cross validation on the training data to determine the best number of estimators needed. The number of estimators (trees) for this set of params was 472. Also, below is the screenshot of Feature Importance based on the booster parameter criteria. Feature Importance is computed based on the number of times it was used to make splits in all generated trees. I found this feature extremely useful as well as interesting to see which feature(s) played an important role in predicting the target variable. In future, for other applications, I can use this feature as part of feature selection exercise.

```
Shape of selected columns train data (1503424, 22)
CPU times: user 1h 5min 58s, sys: 3.09 s, total: 1h 6min 1s
Wall time: 1h 6min 1s
```



Once I had this, my next step was to to use grid search to further fine tune some booster parameters (especially max_depth and min_child_weight to avoid over fitting). Due to limitations of the aws instance, the grid search did not successfully run to completion. I terminated the run after 9 hours. Unfortunately, there were no intermediate results that I could have used. For pedagogical purposes, I ran the grid search on a small training set (~5000 records). Below is the snapshot of the optimized scores of the grid search. From the output of the optimized scores, the combination of 3 and 5 for max_depth and min_child_weight respectively, had the lowest score. I decided to use these values for my Model 1

```
In [245]: if flg_mdl_1 and flg_mdl_1_xgb_gridsearch:
              optimized_GBM.grid_scores_

Out[245]: [mean: -0.09520, std: 0.01919, params: {'min_child_weight': 3, 'max_depth': 3},
           mean: -0.09056, std: 0.02037, params: {'min_child_weight': 5, 'max_depth': 3},
           mean: -0.09852, std: 0.01888, params: {'min_child_weight': 3, 'max_depth': 5},
           mean: -0.09806, std: 0.02859, params: {'min_child_weight': 5, 'max_depth': 5},
           mean: -0.09412, std: 0.01474, params: {'min_child_weight': 3, 'max_depth': 6},
           mean: -0.10422, std: 0.02328, params: {'min_child_weight': 5, 'max_depth': 6}]
```

Model 2:

- Number of epochs to train the NN: As this was a fairly simple NN (2 layers with 64 nodes each), started small (around 15 epochs) and went upto 45 epochs. For multiple runs, noticed that the ‘val_loss’ metric stopped improving anywhere after 20 epochs. So, decided to use 30 epochs.

- Number of SVD components to use from the tf-idf matrix: Based on sklearn recommendation (http://scikit-learn.org/stable/modules/generated/sklearn.decomposition.TruncatedSVD.html) ,used 100 SVD components derived from the TF-IDF matrix. Also, experimented with the using 125 components. Didn't see any difference in the RMSE score. Decided to use 125 as my final value.

Model 3 - processing image data:

Processing the entire training image data (1.3 million images) turned out to be a very resource intensive task.

Converting and storing the image arrays:

With the large volume of images in the training dataset, I was not able to process and store the image arrays in the RAM. My initial approach was to use a different instance of aws with bigger RAM. I changed the aws instance from p2.xlarge instance with 60 GiB of RAM to p2.8xlarge instance with 488 GiB of RAM , but I still ran into memory constraints. Then,I started exploring options available in python to handle large volume datasets and learned about h5py. Used h5py to convert the images to image arrays and stored the hp5y file on hard disk. This was a very time consuming task. It took about 6-8 hours to process the training dataset (~1.3 M images) and testing (~500 K images) dataset and used about 600GB of hard disk.

Next, I wrote helper methods (e.g Generator method that reads from the h5py file into RAM during training) to get chunks of data that the RAM can handle.

Hurdles with the volume of training data

With training data processed and stored as hdf5 file and functions to read the file in chunks, I started to train the CNN. Unfortunately, a single epoch was taking more than a few hours (I am speculating that it was the disk io). After letting it run overnight and not seeing very promising results (i.e., the net was running its second epoch), I decided to terminate the process. Because at this rate, training would have taken days and my aws expenses were going to be really high.

Next, I decided to use a smaller training data set. I was hoping that about 500K images will work faster. However, this did not speed up the process that much either. The runtime was still in the order of an hour or so for a single epoch.

As my final attempt, I used a very small training data set (about 5000 images). I chose this number because, the Dog Classifier project used about 6000 images and the current aws instance (p2.xlarge) ran quickly on this set. I know the accuracy may not be good (as the training data set sample is about 0.3%) and the combined model may not be very predictive. But, I wanted to do this as a learning exercise. As expected, in the next section, you will notice that this model (trained on very limited amount of data) performed very poorly.

(As a side note, this exercise made me appreciate the idea of transfer learning more, where a user can take and apply the learnings of pre-trained network.I will be exploring this option as a future improvement to the project)

IV. Results

Below table summarizes the various models used and the RMSE score generated on the test data. As this is an active Kaggle competition, had to submit the prediction scores on the test data to Kaggle.com to get the RMSE score for all the models I used.

The order of rows, reflects the order in which I built models, evaluated and combined them piecemeal. As soon as I had Model 2, I built a combined model that used only outputs from Model 1 and Model 2. I labeled this ‘Combined Model 1 and 2’.

When combining the two models, I considered XGB, NN and a linear regression models to see which model performed the best. From the results, it can be seen that they all compared very similarly, with XGB performing slightly better compared to the other two models.

During evaluation of how best to combine Model 1 and 2, I explored an alternate approach, where instead of combining outputs of the two models, combine the data of Model 1 and Model 2 and use a single model to predict the target variable. This is the ‘Alternate combined model 1 and 2 data’. The RMSE score came close to the ‘Combined Model 1 and 2’, but did not perform as well as the combined model.

Also, from the table below, it can be seen that the individual models by themselves (Model 1 or Model 2) did not have a good RMSE score. But when the results from Model 1 and 2 were combined, the RMSE scores started to decrease. This reflects my initial expectation that model should perform better with every new addition of data/information (textual and images).

Model	Description	Learner	Num. Training and Validation records	Num. Testing records	RMSE score
Benchmark	Used tabular data from train.csv. Did not consider title and description column	Decision Tree Regressor	1503434	508438	0.2410
Model 1	Used tabular data from train.csv. Included SVD components from the 'title' column	XGB Regressor	1503434	508438	0.2302
Model 2	Used ~125 SVD components of the 'description' column	Neural Net	1503434	508438	0.2450
Combined Model 1 and 2	Used individual outputs from Model 1 and 2 as inputs to predict the final target value	XGB Regressor	1503434	508438	0.2293
Combined Model 1 and 2	Used individual outputs from Model 1 and 2 as inputs to predict the final target value	Neural Net	1503434	508438	0.2294
Combined Model 1 and 2	Used individual outputs from Model 1 and 2 as inputs to predict the final target value	Linear Regressor	1503434	508438	0.2295
Alternate	This model	XGB	1503434	508438	0.2297

combined Model 1 and 2 data	combined the tabular data input with the top 20 svd components of the description data	Regressor			
Model 3	Used a very small sample of Images from train.csv	CNN	4000	508438	0.3032
Combined Model 1, 2 and 3	Used outputs from model 1,2,3 as inputs to predict the final target value	XGB Regressor	4000	508438	0.2533

Robustness of the best model (‘Combined Model 1 and 2’):

I did cross validation on the ‘Combined Model 1 and 2’ with 10 folds to test the robustness of the best model from above. Below is screen shot of the neg_mse_score from each fold, average neg_mse_score (-0.0496) and the RMSE (0.2227). If you look at the results table, you will notice the RMSE on test data set is in the same range as the CV RMSE score. This indicates that this model is fairly robust and not overfitted to train data.

```
CV results:  [-0.04932955 -0.04985597 -0.04941303 -0.04934463 -0.0494912  -0.04950887
 -0.04948246 -0.04952055 -0.05006286 -0.04973774]
MSE: -0.0496 (+/- 0.0004)
RMSE : 0.2227
CPU times: user 4min 11s, sys: 0 ns, total: 4min 11s
Wall time: 4min 8s
```

V. Conclusion

When I first read about the project, the most appealing part of the project was that it had various types of data to work with (tabular, textual, image). Apart from seeing an opportunity to work with and explore different techniques that worked for particular data types (e.g. CNN for image data, NN for analyzing textual data), I wanted to validate that data when viewed as individual sources, may not be very predictive, but combined together can tell a rich story. For example, from the table above, it can be seen that individual RMSE scores of Model 1, 2 and 3 were not that stellar (exception being Model 1) compared to the Benchmark model. However, when they were used together, the overall predictiveness improved. This can be clearly seen from the RMSE score of the 'Combined Model 1 and 2'.

During the model development phase, I was very encouraged with how the RMSE score was improving whenever a different facet of data was being added (i.e., benchmark only considered tabular data, whereas Combined model considered both tabular and description data) to predict the target variable.

Below is a random sample of predicted probability of the test data. item_id is the unique ad identifier, deal_probability_mdl_1 is the predicted target value from Model 1 and deal_probability_cmb_mdl is the predicted target value from the combined model.

As you will notice, the target_variable probability of the combined model is consistently higher compared to single model (Model 1).

	item_id	deal_probability_mdl_1	deal_probability_cmb_mdl
259915	341b476d37a5	0.486519	0.556968
248900	8d2e6449e00f	0.068060	0.071278
504349	83de3bf6a702	0.083199	0.087445
413475	91321f142b2d	0.085966	0.092986
305765	47b3d9cb89bb	0.151695	0.167980
476206	d8dda03872e5	0.184616	0.126497
150900	3372be1a89e0	0.067741	0.069216
419589	314c3316fd23	0.241818	0.273594
358730	aee6cc9f0bd1	0.125099	0.121168
451727	ad4b2df87fa6	0.144086	0.132919

I was very positive that by adding image data, I would certainly improve the test RMSE score. Unfortunately, due the challenges outlined above, I was not able to validate my hypothesis.

This leads me into future improvements for this project. As a future improvement, I am going to do literature survey on availability of pre-trained CNNs that when given an image can generate a score/grade that rates the image in-terms of its ‘quality’. At this point, I am not clear on how best to define ‘quality’. But I am hoping, this pre-trained CNN would have considered things like brightness, centered image, etc to rank the image. I would use this score as the input to the combined model and train the combined model.

Also, when reading about XGB model, I came across another similar Tree ensemble model called Light GBM from microsoft that trains faster, has low memory usage and better accuracy than most of the boosting algorithms (https://www.analyticsvidhya.com/blog/2017/06/which-algorithm-takes-the-crown-light-gbm-vs-xgboost/). I want to compare Light GBM performance to XGB performance on Model 1 data in terms of RMSE score as well as see if I could perform effective grid search on Light GBM to better tune the parameters of the model.