Binary Classification via Iterative Learning

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0.1 Definition

Please refer to notebook `1 Definition`.

0.1.1 Problem Statement

In this Kaggle competition, Red Hat seeks an optimal algorithm for using information about a given action and information about a given customer to predict the customer's behavior with regard to that action. A completed product will take the form of a csv with two items per row - an `action_id` from the test set, and a predicted outcome from the set $0, 1$.

The following is a sample of the required format for a solution submission:

```
$ head data/sample_submission.csv

activity_id,outcome
act1_1,0
act1_100006,0
act1_100050,0
act1_100065,0
act1_100068,0
act1_100100,0
```

Data is provided in the form of three separate data sets encoded as CSV:

- `people.csv`
- `act_train.csv`
- `act_test.csv`.

We will store our data in two tables in a PostgreSQL Database. The `action` (`act_train.csv`) table makes reference to the `people` (`people.csv`) table. Beyond this, the sets have been scrubbed of any domain specific knowledge. Rather attributes are referred to generically as `char_1`, `char_2`, etc. As such the competition presents an interesting challenge, in which domain knowledge is completely useless. The competition is in essence a "pure machine learning problem."

0.1.2 Approach

We take the following approach to completing this task:

1. Seed a PostgreSQL database with the three csv files.

2. One-Hot Encode the data and store the one-hot encoded vector as an array in the `action` table
3. Train and Assess a Series of Learners
    - try learning via random search
    - try learning via random local search
    - try learning via stochastic gradient descent
    - try learning through a multi-layer neural network

Note that while the Kaggle Challenge includes a set of test-data, for the purposes of this study we will be holding a separate test set aside that we are able to run our own local accuracy metrics. At the time of this writing, the competion is closed to new submissions.

To prevent overfitting, we will include a regularization penalty in our model.

0.1.3 Metrics

We will look at three different properties of our test set in order to measure the success of our learner:

1. a confusion matrix
2. accuracy
3. F1 Score

Our task is one of classification. The confusion matrix is specifically designed to show the success of a classifier by showing the number of times it correctly and incorrectly identified each target class. The accuracy aims to capture the success of the classifier by calculating a normalized count of the number of successful prediction. The F1 score is a third metric for classification which can be thought of as a weighted average of the precision and recall. The confusion matrix will provide a handy visual for examining our learners, whereas the accuracy and the F1 score will provide a numerical metric which can be optimized.

We will assess the learner against the test set throughout the training process as a way of assessing the development of our learner. However, the results of the development of the assessment will not be uses for training and can thus be used repeatedly as an impartial measure of progress.

0.1.3.1 Infrastructure

We have designed a special infrastructure geared toward a "back-end"/server-side implementation of our processes. This system uses Jupyter notebooks as its main interface, thought it is possible to interface with the system via the terminal.

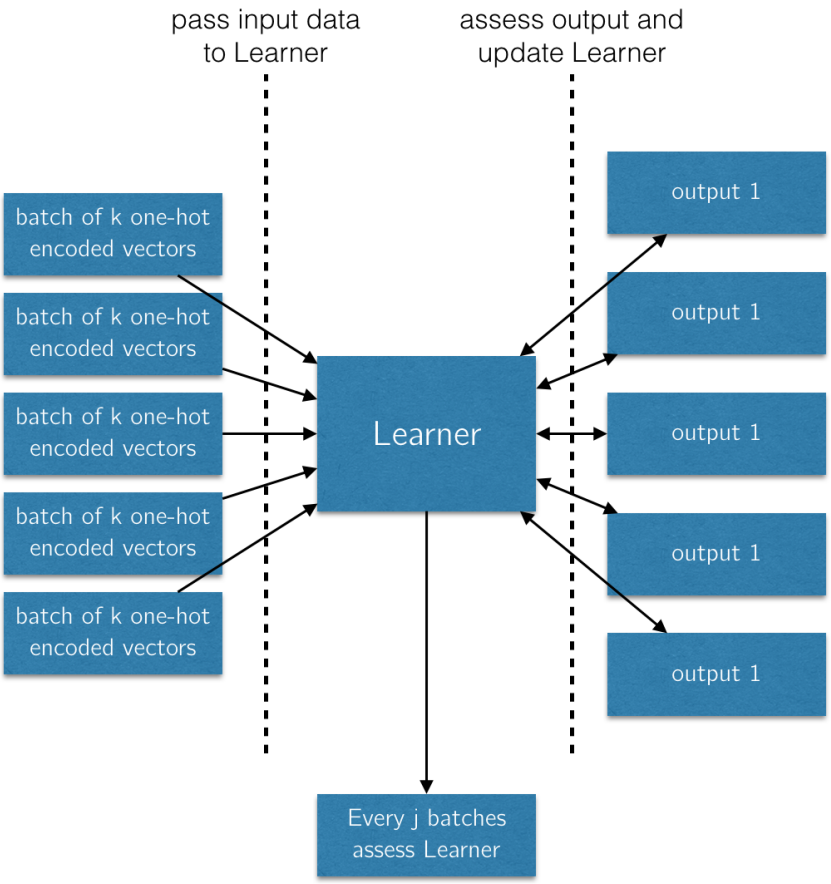


Figure 1: Learner Training and Assessment

Additionally, a browser-based control panel exists for tracking the progress of our workers. We use to data management systems, a PostgreSQL database and Redis. Finally, we have a worker layer of n scalable worker cpus built using Python's `rq` framework.

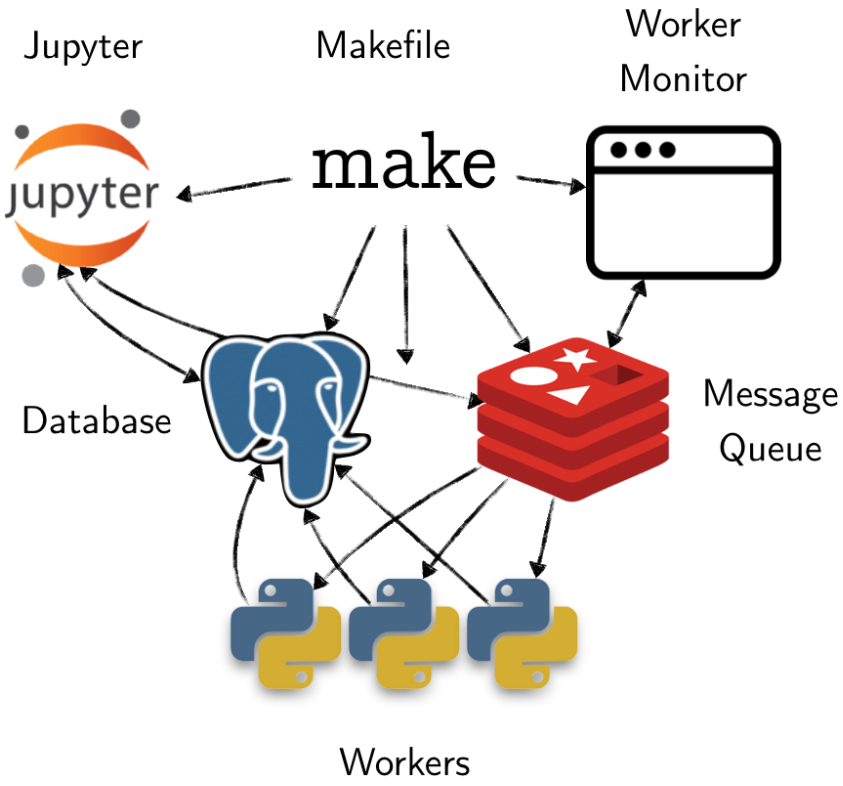


Figure 2: Infrastructure

0.2 Preliminary Data Analysis

0.2.1 Connecting to PostgreSQL

Please refer to notebook `2.01 Preliminary Data Analysis - Connecting to PostgreSQL`.

We store all included data in a PostgreSQL database. By and large, we access this database using the `psycopg2` library. Here, we make use of a development

pattern we will use throughout the project in which more complicated are abstracted into modules in `lib`. Here, we import `connect_to_postgres` from `lib/helpers/database_helper.py` and use it to connect to our database. Then, we run a simple query on the database, verifying that all is functioning well.

```
>>> from os import chdir; chdir('../')
>>> from lib.helpers.database_helper import connect_to_postgres
>>> conn, cur = connect_to_postgres()
>>> cur.execute("SELECT COUNT(*) FROM people"); print(cur.fetchone())
>>> cur.execute("SELECT COUNT(*) FROM action"); print(cur.fetchone())
(189118,)
(2695978,)
>>> conn.close()
```

0.2.2 Data Exploration

The data to be used here consists of three datasets:

- `people.csv` sample
- `act_train.csv` sample
- `act_test.csv` sample

We will do the following to analyze the datasets.

1. seeding the database
2. basic postgres descriptor (`\d+`)
3. define the basic structure - rows, columns, data types
4. identify unique labels for each column and the counts for each label
5. run aggregates on columns - mean, median, max, min
6. identify duplicate records, if they exist
7. search for NULL data
8. create histograms of data

0.2.3 Seeding the Database

This is handled during the building of the Docker image for our PostgreSQL database and is written into our database Dockerfile.

In order to run the commands in this `Dockerfile` we use the `docker-compose` tool to build our image.

```
$ docker-compose build
```

During the building of the image, any `.sql` or `.sh` files located in `/docker-entrypoint-initdb.d` will be executed. We have defined the tables we will be using in the `tables.sql` file. The structure will be shown in a moment when we run the postgres descriptors. The full structure can be viewed in the seeding file here. This functionality is part of the PostgreSQL public Docker image.

0.2.4 Basic PostgreSQL Descriptors

Having built and run our images, we now have a running PostgreSQL database that has been seeded with our csv data.

0.2.4.1 Descriptor for database

We use the PostgreSQL descriptor command to display basic attributes of our database.

```
postgres=## \d+
                          List of relations
 Schema |      Name       | Type  |  Owner   |  Size   | Description
--------+-----------------+-------+----------+---------+-------------
 public | action          | table | postgres | 235 MB  |
 public | people          | table | postgres | 30 MB   |
```

0.2.4.2 Descriptor for `action` table

We can repeat the same for a particular table. The tables have been trimmed so as not to show columns of repeating type.

```
postgres=## \d+ action
           Table "public.action"
    Column    |            Type             |
--------------+-----------------------------+
 people_id    | text                        |
 act_id       | text                        |
 act_date     | timestamp without time zone |
 act_category | text                        |
 act_char_1   | text                        |
                  ...
 act_char_10  | text                        |
 act_outcome  | boolean                     |
Indexes:
    "action_pkey" PRIMARY KEY, btree (act_id)
Foreign-key constraints:
    "action_people_id_fkey" FOREIGN KEY (people_id) REFERENCES people(people_id)
```

0.2.4.3 Descriptor for people table

```
postgres=## \d+ people
               Table "public.people"
   Column    |            Type             | Modifiers |
-------------+-----------------------------+-----------+
 people_id   | text                        | not null  |
 ppl_char_1  | text                        |           |
 ppl_group_1 | text                        |           |
 ppl_char_2  | text                        |           |
 ppl_date    | timestamp without time zone |           |
 ppl_char_3  | text                        |           |
                           ...
 ppl_char_9  | text                        |           |
 ppl_char_10 | boolean                     |           |
 ppl_char_11 | boolean                     |           |
 ppl_char_12 | boolean                     |           |
                           ...
 ppl_char_37 | boolean                     |           |
 ppl_char_38 | real                        |           |
Indexes:
    "people_pkey" PRIMARY KEY, btree (people_id)
Referenced by:
    TABLE "action" CONSTRAINT "action_people_id_fkey"
        FOREIGN KEY (people_id) REFERENCES people(people_id)
```

0.2.5 Define the Basic Structure

Please refer to notebook 2.05 Preliminary Data Analysis - Define the Basic Structure.

The number of rows in a set can be identified by a query using the `COUNT()` function. Our test and training sets can be identified by the fact that the test set has `NULL` values in the `act_outcome` column.

0.2.5.1 Number of Rows in database tables

database	number of rows	number of training rows
`people`	189118	N/A
`action`	2695978	498687

0.2.5.2 Number of Columns per Data Type

database	text	boolean	timestamp	real
`people`	11	28	1	0
`action`	13	1	1	1

0.2.6 Identify Unique Labels

0.2.6.1 Number of Unique Labels for `people`

label	unique
people_id	189118
ppl_group_1	34224
ppl_date	1196
ppl_char_1	2
ppl_char_2	3
ppl_char_3	43
ppl_char_4	25
ppl_char_5	9

label	unique
ppl_char_6	7
ppl_char_7	25
ppl_char_8	8
ppl_char_9	9

Additionally we do not show the final group of columns for the following reasons. `ppl_char_10` through `ppl_char_37` are boolean and have only two labels - `TRUE` and `FALSE`.

`ppl_char_38` is a continuous valued column.

0.2.6.2 Number of Unique Labels for `action`

Again we first show columns that have too many labels. However, upon second consideration we should use the column `act_category`.

label	unique
act_id	2695978
act_date	411
act_category	7
act_char_1	51
act_char_2	32
act_char_3	11
act_char_4	7
act_char_5	7
act_char_6	5
act_char_7	8
act_char_8	18
act_char_9	19
act_char_10	6969

We do not show the outcome `act_outcome` because it is boolean.

0.2.7 Run Aggregates on Columns

Next we take the average of our boolean columns. Note that all of them skew to the negation, most of them heavily so. The only exception is `act_outcome` which, while still toward the negation, is closer to the middle.

label	mean
ppl_char_10	(0.2509)
ppl_char_11	(0.2155)
ppl_char_12	(0.2403)
ppl_char_13	(0.3651)
ppl_char_14	(0.2598)
ppl_char_15	(0.2695)
ppl_char_16	(0.2821)
ppl_char_17	(0.2920)
ppl_char_18	(0.1876)
ppl_char_19	(0.2847)
ppl_char_20	(0.2291)
ppl_char_21	(0.2850)
ppl_char_22	(0.2911)
ppl_char_23	(0.2985)
ppl_char_24	(0.1904)
ppl_char_25	(0.3278)
ppl_char_26	(0.1670)
ppl_char_27	(0.2381)
ppl_char_28	(0.2889)
ppl_char_29	(0.1683)
ppl_char_30	(0.2069)
ppl_char_31	(0.2786)
ppl_char_32	(0.2849)
ppl_char_33	(0.2178)
ppl_char_34	(0.3565)
ppl_char_35	(0.2103)
ppl_char_36	(0.3437)

label	mean
ppl_char_37	(0.2855)
act_outcome	(0.4440)

Then we take the average, maximum, and minimum of the single real-valued column.

```
SELECT AVG(ppl_char_38), MAX(ppl_char_38), MIN(ppl_char_38) FROM people;
       avg        | max | min
------------------+-----+-----
 50.3273987669074 | 100 |   0
(1 row)
```

0.2.8 Identify Duplicate Records

Note that there are 189118 `people_id` values, one for each row. We can take this to mean that there are no duplicate entries in the `people` dataset. The same is true with actions with 2695978 unique `act_id` values.

0.2.9 Search for NULL Data

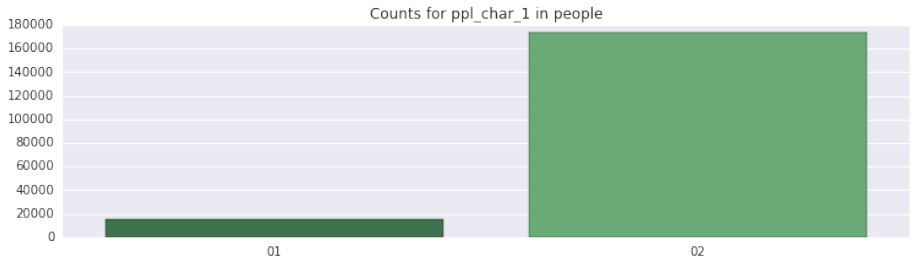
There is null data in these datasets, in two locations. There are null values in the boolean variables attached to the `action` table. We will be handling this data, however, when we process the data for handoff to the neural network. Additionally, there are null values in the `act_outcome` column, but this is functional as a null value in this field signifies a **test** action as opposed to a **train** action.

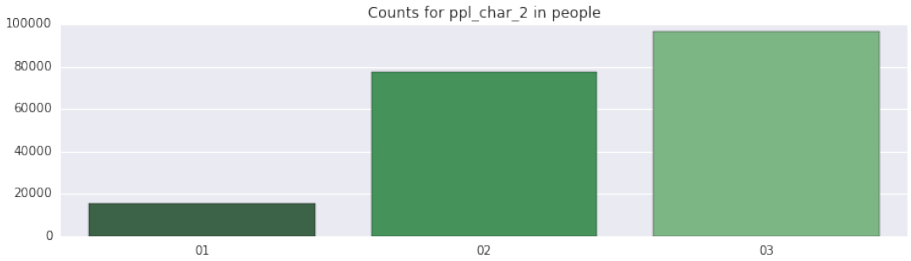
0.2.10 Exploratory Visualiztion

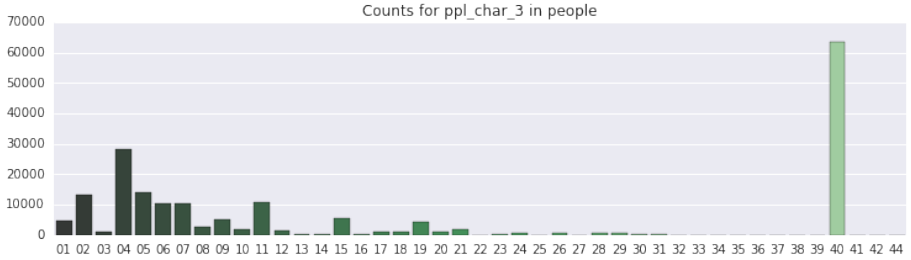
Please refer to notebook 2.10 Preliminary Data Analysis - Create Histograms of Data.

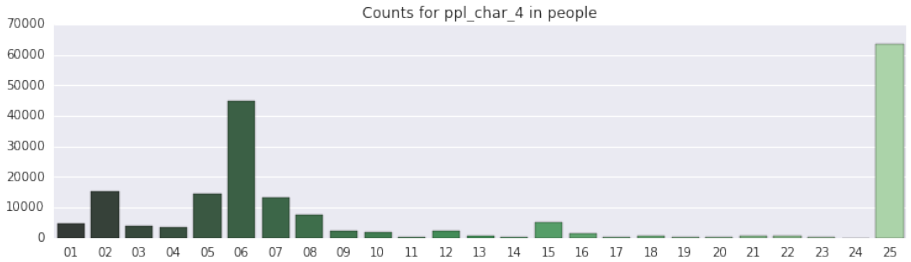
Finally, we use the Python library seaborn to create plots of our data as histograms. We import a method `bar_plot` to present a histogram for each categorical parameter.

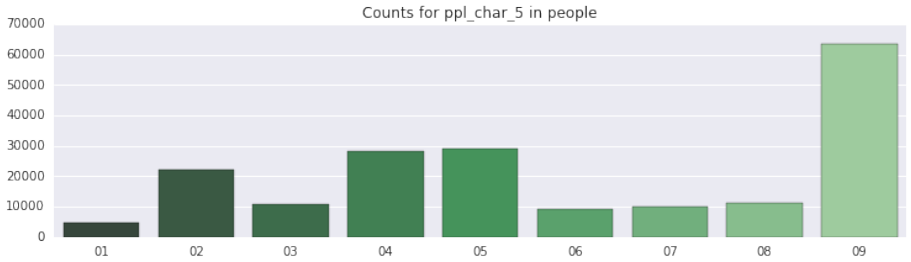
```
>>> from os import chdir; chdir('../')
>>> from lib.helpers.plot_helper import bar_plot
>>> bar_plot('ppl_char_1','people')
>>> bar_plot('ppl_char_2','people')
>>> bar_plot('ppl_char_3','people')
>>> bar_plot('ppl_char_4','people')
>>> bar_plot('ppl_char_5','people')
>>> bar_plot('ppl_char_6','people')
>>> bar_plot('ppl_char_7','people')
>>> bar_plot('ppl_char_8','people')
>>> bar_plot('ppl_char_9','people')
>>> bar_plot('act_char_1','action')
>>> bar_plot('act_char_2','action')
>>> bar_plot('act_char_3','action')
>>> bar_plot('act_char_4','action')
>>> bar_plot('act_char_5','action')
>>> bar_plot('act_char_6','action')
>>> bar_plot('act_char_7','action')
>>> bar_plot('act_char_8','action')
>>> bar_plot('act_char_9','action')
```

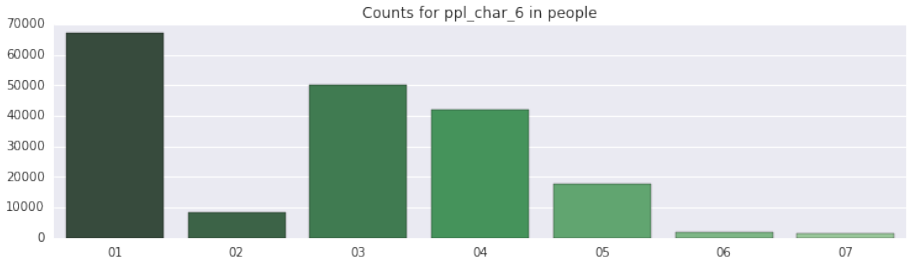


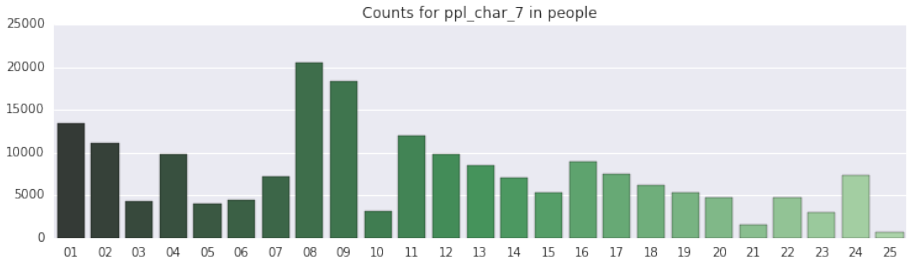

Counts for ppl_char_2 in people
100000
80000
60000
40000
20000
0
01
02
03

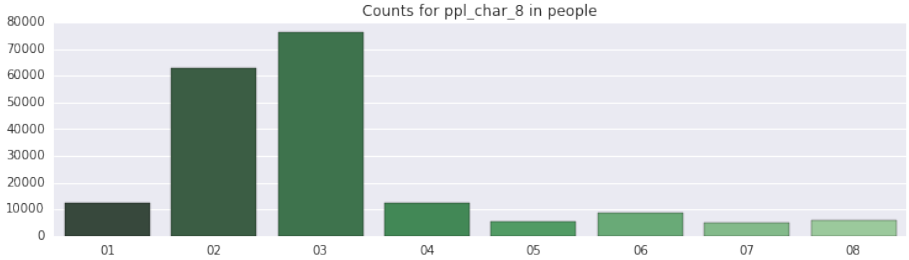

Counts for ppl_char_3 in people
70000
60000
50000
40000
30000
20000
10000
0
01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 44

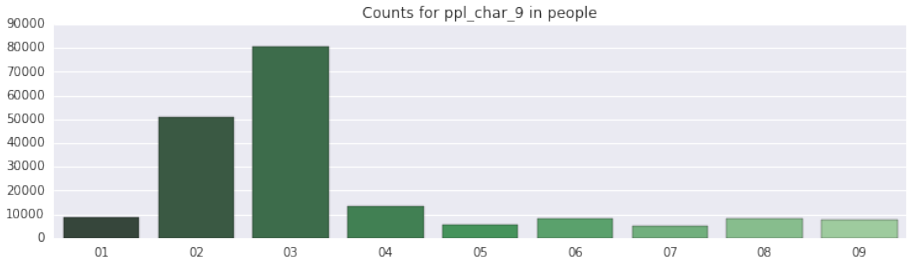

Counts for ppl_char_4 in people
70000
60000
50000
40000
30000
20000
10000
0
01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25

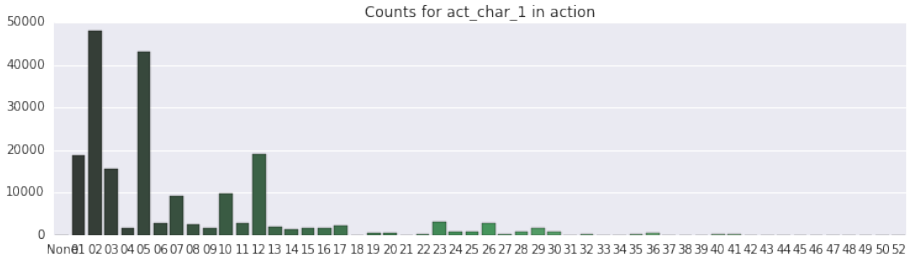

Counts for ppl_char_5 in people
70000
60000
50000
40000
30000
20000
10000
0
01
02
03
04
05
06
07
08
09

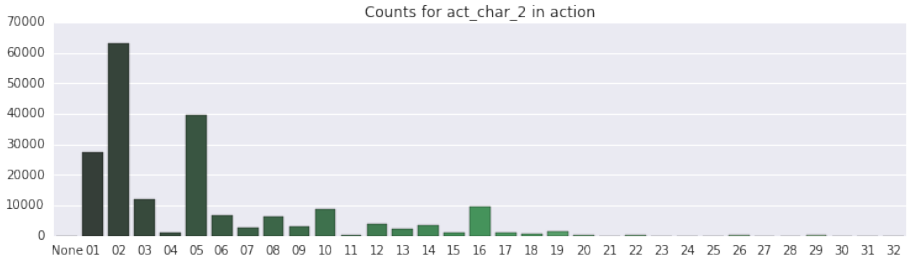

Counts for ppl_char_6 in people
70000
60000
50000
40000
30000
20000
10000
0
01
02
03
04
05
06
07

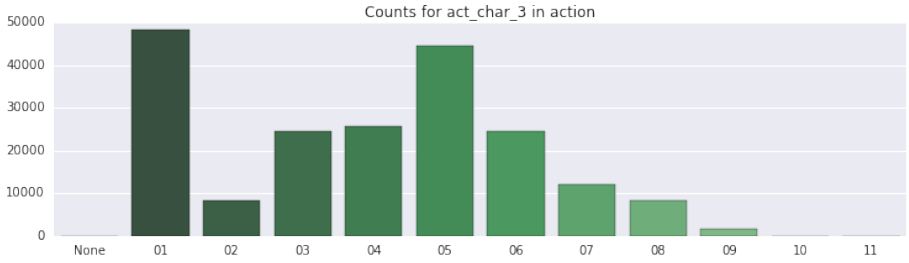

Counts for ppl_char_7 in people
25000
20000
15000
10000
5000
0
01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25

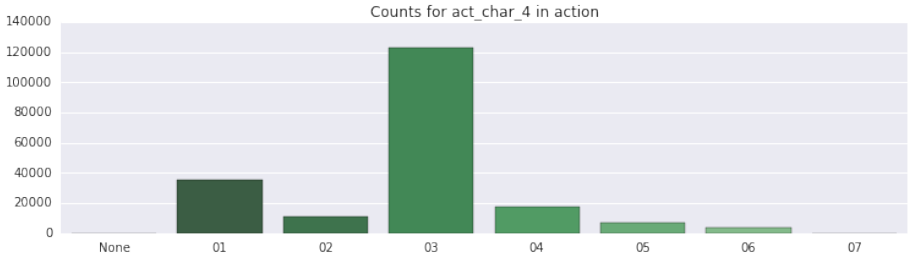

Counts for ppl_char_8 in people
80000
70000
60000
50000
40000
30000
20000
10000
0
01 02 03 04 05 06 07 08

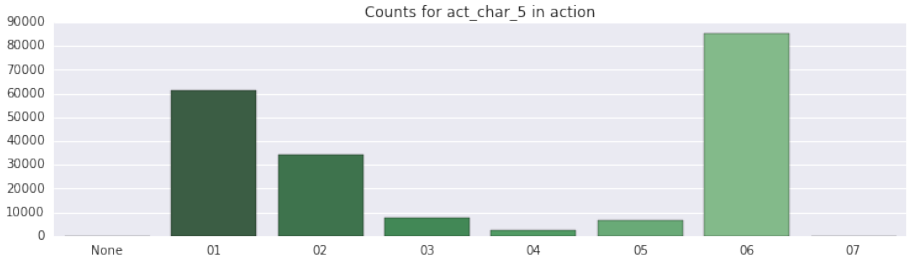

Counts for ppl_char_9 in people
90000
80000
70000
60000
50000
40000
30000
20000
10000
0
01 02 03 04 05 06 07 08 09

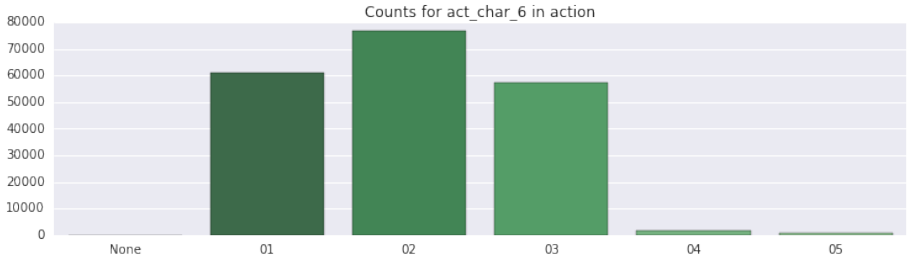

Counts for act_char_1 in action
50000
40000
30000
20000
10000
0
None 01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 52

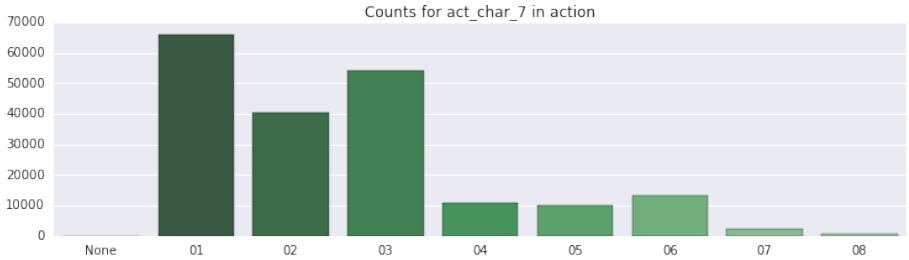

Counts for act_char_2 in action
70000
60000
50000
40000
30000
20000
10000
0
None 01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32

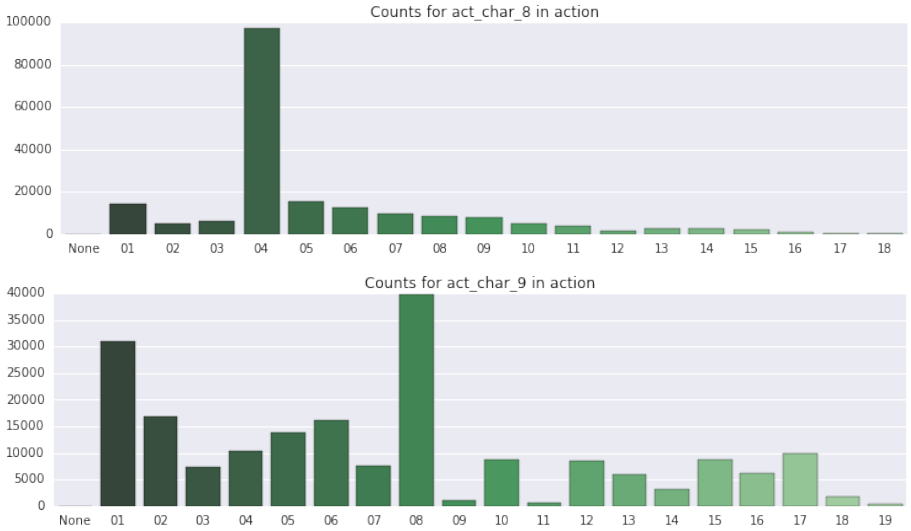

Counts for act_char_3 in action
50000
40000
30000
20000
10000
0
None
01
02
03
04
05
06
07
08
09
10
11


Counts for act_char_4 in action
140000
120000
100000
80000
60000
40000
20000
0
None
01
02
03
04
05
06
07


Counts for act_char_5 in action
90000
80000
70000
60000
50000
40000
30000
20000
10000
0
None
01
02
03
04
05
06
07


Counts for act_char_6 in action
80000
70000
60000
50000
40000
30000
20000
10000
0
None
01
02
03
04
05


Counts for act_char_7 in action
70000
60000
50000
40000
30000
20000
10000
0
None
01
02
03
04
05
06
07
08



0.3 Algorithms and Techniques

0.3.1 One-Hot Encoding

Please refer to notebook `3.01 Algorithms and Techniques - One-Hot Encoding Example`.

We will use the One-Hot Encoding algorithm to convert our categorical data to numerical data. It may be tempting to merely convert our categories to numbers i.e. `type 01` $\rightarrow$ 1, `type 02` $\rightarrow$ 2, however, such an encoding of data implies a linear relationship between our categories, where there may be none.

> In one-hot encoding, a separate bit of state is used for each state. It is called one-hot because only one bit is "hot" or TRUE at any time. (Harris, David, and Sarah Harris. Digital design and computer architecture. Elsevier, 2012.)

This algorithm is also referred to as 1-of-K encoding. An example will be helpful in illustrating the concept.

0.3.1.1 One-Hot Encoding Example

```
>>> import numpy as np
>>> from os import chdir; chdir('../')
>>> from lib.helpers.database_helper import connect_to_postgres
>>> conn, cur = connect_to_postgres()
>>>
>>> cur.execute("SELECT ppl_char_1,ppl_char_2 FROM people LIMIT 10")
>>> this_row = cur.fetchone()
>>> one_hot = []
>>> while this_row:
        one_hot.append([
            this_row[0] == 'type 1',
            this_row[0] == 'type 2',
            this_row[1] == 'type 1',
            this_row[1] == 'type 2',
            this_row[1] == 'type 3',
        ])
    this_row = cur.fetchone()
>>> print(np.array(one_hot, dtype=int))
[[0 1 0 1 0]
 [0 1 0 0 1]
 [0 1 0 0 1]
 [0 1 0 0 1]
 [0 1 0 0 1]
 [0 1 0 0 1]
 [0 1 0 1 0]
 [0 1 0 0 1]
 [0 1 0 0 1]
 [0 1 0 0 1]]
```

Here, we select two columns from our database. For each available type for each column, we do a Boolean check and then cast this check to an integer. The result is that for a given group of columns corresponding to a single column in our original database, there will be a single `1` and the remainder will be `0`. We use one-hot coding because the categorical and boolean nature of the vast majority of our data lends itself to this technique.

0.3.2 Linear Classification via Neural Network

Linear classification will be the core algorithm upon which we will build our neural network classifier. We borrow heavily for this approach from Andrej Karpathy's notes for his Convolutional Neural Networks course:

The approach will have two major components: a **score function** that maps the raw data to class scores, and a **loss function** that quantifies the agreement between the predicted scores and the ground truth labels.

0.3.2.1 Score Function

We will develop a score function that maps input vectors to class scores

$$f : \mathbb{R}^{\mathbb{D}} \mapsto \mathbb{R}^2$$

where D is the dimension of our one-hot encoded vectors and 2 represents the 2 classes of our binary classifier. Then,

$$f(x_i, W, b) = Wx_i + b = y$$

where x_i is a particular input vector, W is a matrix of weights (dimension $2 \times n$), b is a bias vector, and y is a score vector with a score for each class.

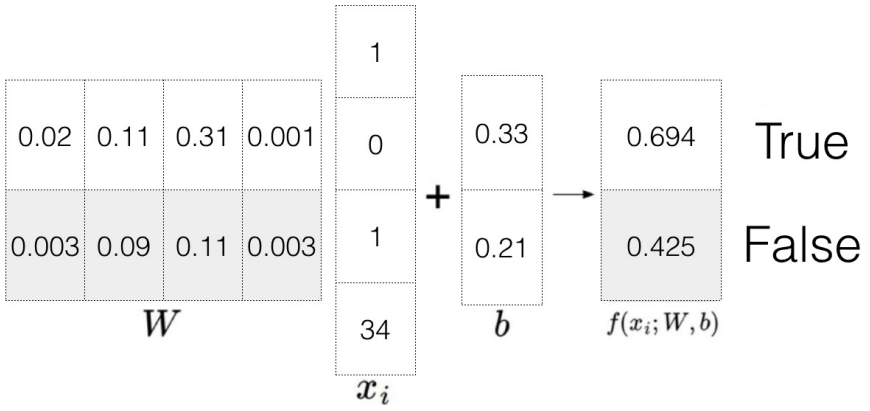


Figure 3: A Linear Classifier

0.3.2.2 Loss Function

Note that of the inputs to our score function we do not have control over the x_is. Instead, we must change W and b to match a set of given ys. To do this we will define a loss function that measures our performance. We will use one of

the most common loss functions the multiclass support vector machine. Here the loss for a given vector is

$$L_i = \sum_{j \neq y_i} \max(0, s_j - s_{y_i} + \Delta)$$

Here, s is the vector result of our score function and y_i is the correct class. Our loss function computes a scalar value by comparing each incorrect class score to the correct class score. We expect the score of the correct class to be at least Δ larger than the score of each incorrect class.

0.3.2.3 Regularization Penalty

It is possible that more than one set of weights could provide an optimal response to our loss function. In order to prioritize the smallest possible weights we will add a regularization penalty to our loss function. Again we will go with a common technique and use the L2 norm.

$$R(W) = \sum_k \sum_l W_{k,l}^2$$

Additionally, including a regularizatiom penalty has the added benefit of helping to prevent overfitting.

0.3.2.4 Final Loss Function

$$L = \frac{1}{N} \sum_i L_i + \lambda R(W)$$

Here, λ is a hyper parameter to be fit by cross-validation and N is a batch size.

0.3.3 Optimization

Possibile methods:

0.3.3.1 Generate a Random Weights Matrix

- we initialize a weights matrix, W

0.3.3.2 Randomly guessing

- we initialize a weights matrix, W_{cur}
- for each vector (or batch of vectors) passed to the learner, we generate a new weights matrix, W_i
- if the new weights, W_i is better in score than W_{cur}, we assign it to W_{cur}

$$W_{cur} \rightarrow W_i$$

- repeat for all of our test vectors

0.3.3.3 Random Local Search

- we initilialize a weights matrix, W
- for each batch of vectors passed, we generate a random matrix, ΔW, of the same dimension as W and scaled by some factor, ν
- we measure the loss against the sum $W + \nu\Delta W$.
- If $W + \nu\Delta W$ has a better score than W, we assign it to W

$$W + \nu\Delta W \rightarrow W$$

- repeat for all of our test vectors

0.3.3.4 Gradient Descent

- compute the best direction along which we should change our weight matrix that is mathematically guaranteed to be the direction of the steepest descent
- the gradient is a vector of derivatives for each dimension in the input space
- calculate the gradient and use this calculation to update the weight matrix

$$W_{new} = W - \nabla L$$

0.3.4 Benchmark

Of note is that, while the outcome is clearly defined by the contest, for the purposes of this project, we will be using a portion of the training set as our benchmark. Of note is that we modified our performance metric during the refinement phase.

As previously noted, we will look at three different properties of our test set in order to measure the success of our learner:

1. a confusion matrix
2. accuracy

3. F1 Score

It is difficult to establish an appropriate benchmark given the nature of the codebase for this project. The vast majority of the code here has been written using pure numpy. As such, we can not hope to compete with the latest libraries such as XGBoost or Keras. A random guessing learner would be successful 50% of the time. We think it a reasonable goal that our methods written by hand achieve an 80% accuracy.

0.3.4.1 Confusion Matrix

A confusion matrix is a table that allows the visualization of the algorithm performance. Each row represents the actual classes of our target variable: 1 or 0. Each column represents the predicted classes of our target variable: 1 or 0. We will then measure the true and false positives as well as the true and false negatives.

0.3.4.2 Accuracy

Accuracy will be calculated in the following manner:

$$\text{Accuracy} = \frac{\text{True Postives} + \text{True Negative}}{\text{Postives} + \text{Negatives}}$$

We will be trying to maximize this value.

0.3.4.3 F1 Score

F1 Score will be calculated as

$$F_1 = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

where

$$\text{precision} = \frac{\text{True Positives}}{\text{True Positive} + \text{False Positives}}$$

and

$$\text{recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

We will be trying to maximize this value.

0.4 Free-Form Visualization

0.4.1 Visualizing the Loss Function

Please refer to notebook `4.01 Exploratory Visualization - Visualizing the Loss Function`.

A relevant visualization to this task is that of the loss function. For this visualizaton, we again turn to Andrej Karpathy's notes.

While we will have difficulty visualizing the loss function over the complete weight space, we can visualize it over a smaller space to begin to understand our approach.

```
>>> import numpy as np
>>> from os import chdir; chdir('../')
>>> from lib.helpers.viz_helper import loss_function_i, \
                                       loss_function_in_a_direction, \
                                       render_all_plots_1d, \
                                       render_all_plots_2d
```

For the purposes of this visualization, let us consider a small random weight matrix $(2, p)$ for a binary classifier, i.e., one weight vector for each classifier.

```
>>> W = np.random.rand(2,7)
```

We then generate a random input vector x (with 6 parameters, and then a trailing bias) and and a vector of outputs.

```
>>> x = np.random.randint(2, size=7)
>>> x[6] = 1
```

Finally, we randomly select a correct outcome for a binary classifier.

```
>>> correct_class = np.random.randint(2)
```

We vary the loss function for a single input with different weights for a single parameter, `param`, then plot this function along various values of `variable_weight` for all of our `params` values.

```
>>> render_all_plots_1d(correct_class,x,W)
```

It is of note that every parameter is convex and can be minimized.

We can also do the same for a comparison of two varied parameters. Again, note that each of these plots is convex.

```
>>> render_all_plots_2d(correct_class,x,W)
```

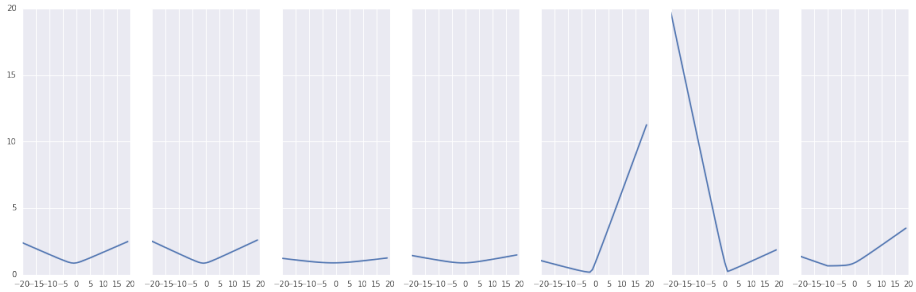


Figure 4: Visualizing Loss Function change along one Parameter

0.5 Data Preprocessing

0.5.1 CSV Manipulation

The dataset was a set provided by Kaggle. As such, it was already well structured and clean. Still, in order to facilitate processing, some work had to be done on the csv data itself.

0.5.1.1 `act_train.csv`

An additional column had to be added to the csv in order to ultimately provide a null space in which to insert our `act_one_hot_encoded` binary value. This was done via the `sed` command line tool by adding a comma to each line.

```
$ sed -e 's/$/,/' -i act_train.csv > new_act_train.csv
```

0.5.1.2 `act_test.csv`

For the test data set, we needed to add two columns, one for the null outcome (test and train are stored in the same table and distinguished by having a true, false or null value) and the same null space in which to insert the `act_one_hot_encoded` binary value.

```
$ sed -e 's/$/,/' -i act_test.csv > new_act_test.csv
```

0.5.1.3 All Sets

Additionally, we wanted to convert all attributes to double digit attributes i.e. `char 1` $\rightarrow$ `char 01`.

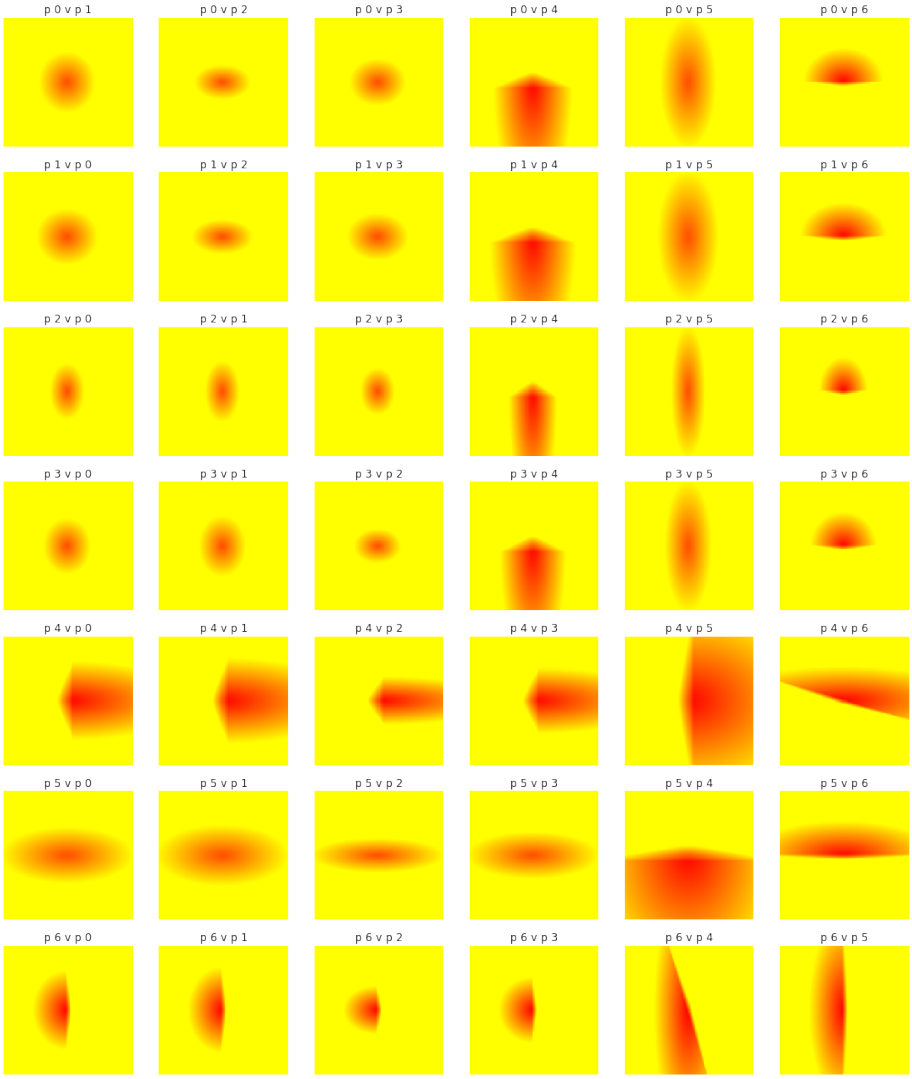


Figure 5: Visualizing Loss Function change against Two Parameters

```
$ sed -e 's/,char (\d),/,char 0\1,/' -i act_train.csv > new_act_train.csv
```

In this section, all of your preprocessing steps will need to be clearly documented, if any were necessary. From the previous section, any of the abnormalities or characteristics that you identified about the dataset will be addressed and corrected here. Questions to ask yourself when writing this section:

0.5.2 One-Hot Encoding

We will be storing our one-hot encoded numpy arrays as binary data in the `action` table column `act_one_hot_encoded`.

0.6 Implementation

0.6.1 Steps to Implementation

1. Seed a PostgreSQL database with the three csv files.
2. One-Hot Encode the data and store the one-hot encoded vector as an array in the `action` table
3. Train and Assess a Series of Learners

0.6.2 Seed a PostgreSQL database with the three csv files.

This step is done at instantiation of the system. Refer to Seeding the Database.

0.6.3 One-Hot Encode the data and store the one-hot encoded vector as an array in the `action` table

Please refer to notebook `6.03 Implementation - Write One-Hot to Action Table`.

```
>>> from os import chdir; chdir('../')
>>> from lib.app import Q
>>> from lib.helpers.database_helper import connect_to_postgres
>>> from lib.helpers.database_helper pull_actions_and_one_hot_encode

>>> for i in range(1000):
        Q.enqueue(pull_actions_and_one_hot_encode, 1000, i*1000)
```

```
>>> conn, cur = connect_to_postgres()
>>> cur.execute("SELECT count(*) FROM action where act_one_hot_encoding is not null;")
>>> cur.fetchone()
(372666,)
```

We have written a library to handle the one-hot encoding of the data. `pull_actions_and_one_hot_encode` does a join on the action and people tables, converts the tables and categories to one-hot encoded data, converts this to a binary `numpy` vector, and writes this binary to the action table, for actions from the action table that do not yet have one-hot encoded vectors.

Note that we are also using our delayed job system to do the conversion. Once jobs have been enqueued, the status of enqueued jobs can be tracked here.

0.6.4 Prediction on Random Weights Matrix With No Training

Please refer to notebook 6.04 Implementation - Prediction on Random Weights Matrix With No Training.

We first establish a baseline competency by examining performance of a totally untrained learner.

```
>>> from os import chdir; chdir('../')
>>> from random import shuffle, seed
>>> from lib.helpers.database_helper import pull_actions, pull_and_shape_batch
>>> from lib.nn.metrics import measure_accuracy, measure_f1_score, correlation_matrix
>>> from lib.nn.functions import random_matrix, predict
```

0.6.4.0.1 Pull Training and Test Rows We `seed` the shuffling mechanism for deterministic results. We then pull a set of 90000 `action_ids` from the action table. We shuffle these ids and designtate the first 75000 as our training set and the last 15000 as our test set. To reiterate, we are not using the Kaggle competitions test set as we do not have the actual outcomes for that set and we can thus not measure the accuracy of our learner.

0.6.4.0.2 Train Learner and Assess Learner Accuracy We are not actually training a learner here. We are merely generating a random matrix of the appropriate size. We then check the accuracy of this random matrix against our test set. This is done four times via the `%%timeit` ipython magic function.

```
>>> seed(42)
>>> action_set = pull_actions(limit=90000,action_type='training')
>>> shuffle(action_set)
```

```
>>> training_set = action_set[:75000]
>>> test_set = action_set[75000:]

%%timeit
>>> # initialize a random_weights matrix
>>> random_weights = random_matrix(2, 7326)
>>> features, outcomes = pull_and_shape_batch(action_ids=test_set)
>>> predicted = predict(random_weights, features)
>>> correlation_matrix(predicted, outcomes)
>>> print(measure_accuracy(predicted, outcomes))
>>> print(measure_f1_score(predicted, outcomes))
```

	act true	act false	totals
pred true	4971	2134	7105
pred false	2118	5777	7895
totals	7089	7911	15000

```
accuracy: 0.716533333333
f1_score: 0.7004368042835001
```

So this purely random matrix performs quite well, achieving an accuracy of 71.7% and an F1-score of 0.700.

We run the same process a second time and third time.

0.6.4.1 Second Pass with a Random Matrix

	act true	act false	totals
pred true	39	1624	1663
pred false	7050	6287	13337
totals	7089	7911	15000

```
accuracy: 0.421733333333
f1_score: 0.008912248628884827
```

0.6.4.2 Third Pass with a Random Matrix

	act true	act false	totals
pred true	0	2	2
pred false	7089	7909	14998
totals	7089	7911	15000

`accuracy: 0.527266666667`

The third pass actually returned a `ZeroDivisionError` for the F1 Score.

0.6.5 Results from Training on a Random Matrix

Training on a random matrix is highly unstable and not a suitable method for learning.

0.7 Refinement

Slightly better than guessing is a pretty poor performance. In order to improve upon our performance, we will try a series of improvements upon our learner in order to obtain better performance.

0.7.1 Learning via Random Search

Please refer to notebook `7.01 Refinement - Learning via Random Search`.

As a first attempt at improvement, we will work in batches through our training set. For each batch we will:

1. generate a random weights matrix
2. evaluate the random weight matrix against the loss function
3. if the loss function is lower than the previous lowest loss function
4. store the loss function as the `best_loss` and the weights matrix as `weights_matrix`

It is of note that we will be doing the training via distributed processing. As such, we can not store the `best_loss` and `weights_matrix` in memory. Instead,

we store the values in Redis. We have written a few methods to handle the storage and retrieval of these values.

- `read_best_loss`
- `read_weights_matrix`
- `write_best_loss`
- `write_weights_matrix`

0.7.1.1 Establish State of Training Session

```
>>> training_set, test_set = pull_training_and_test_sets(limit=700000,split=.99)
>>> features, outcomes = pull_and_shape_batch(action_ids=test_set)
>>> initialize_training_session()
>>> batch_size = 50
>>> for i in range(int(len(training_set)/batch_size)):
>>>     Q.enqueue(train_via_random_search,
>>>               action_ids=training_set[i*batch_size:(i+1)*batch_size],
>>>               gamma=0.001)
>>> counts, f_1_scores, \
>>>     accuracies, \
>>>     loss_values = prepare_plot_vectors(features,
>>>                                        outcomes,
>>>                                        length=int(len(training_set)/batch_size))
```

0.7.1.2 Assess Results

This method, using a batch size of 50 and 700000 samples yielded

- Accuracy: 0.803451
- F1 Score: 0.810321

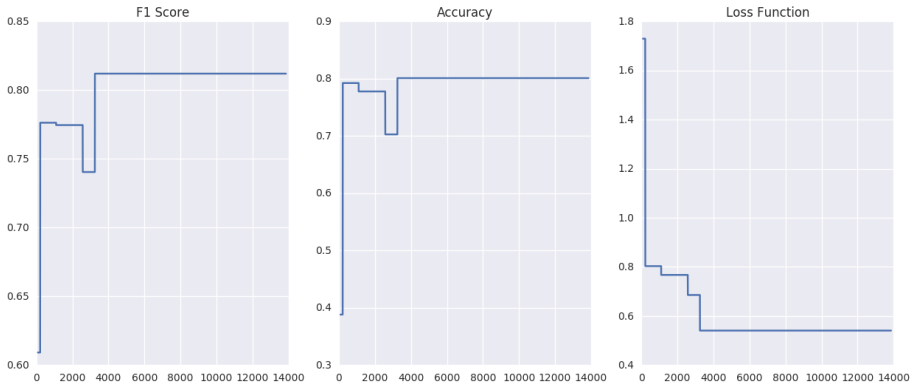


Figure 6: Training via Random Search

0.7.2 Learning via Random Local Search

Please refer to notebook 7.02 Refinement - Learning via Random Local Search.ipynb.

Next, we attempt to improve our initial random matrix via microchanges in the local vicinity. Again, we will work in batches through our training set. For each batch we will:

1. generate a random weights matrix delta
2. add the delta to our current weights matrix
3. evaluate the temporary weight matrix against the loss function
4. if the loss function is lower than the previous lowest loss function
5. store the loss function as the `best_loss` and the temporary weights matrix as `weights_matrix`

0.7.2.1 Establish State of Training Session

```
>>> training_set, test_set = pull_training_and_test_sets(limit=700000,split=.99)
>>> features, outcomes = pull_and_shape_batch(action_ids=test_set)
>>> initialize_training_session()
>>> batch_size = 50
>>> for i in range(int(len(training_set)/batch_size)):
>>>     Q.enqueue(train_via_random_local_search,
>>>               action_ids=training_set[i*batch_size:(i+1)*batch_size],
>>>               gamma=0.001)
>>> counts, f_1_scores, \
>>>     accuracies, \
>>>     loss_values = prepare_plot_vectors(features,
```

```
>>>                                          outcomes,
>>>                                          length=int(len(training_set)/batch_size))
```

0.7.2.2 Assess Results

This method, using a batch size of 50 and 700000 samples yielded

- Accuracy: 0.590684
- F1 Score: 0.668573

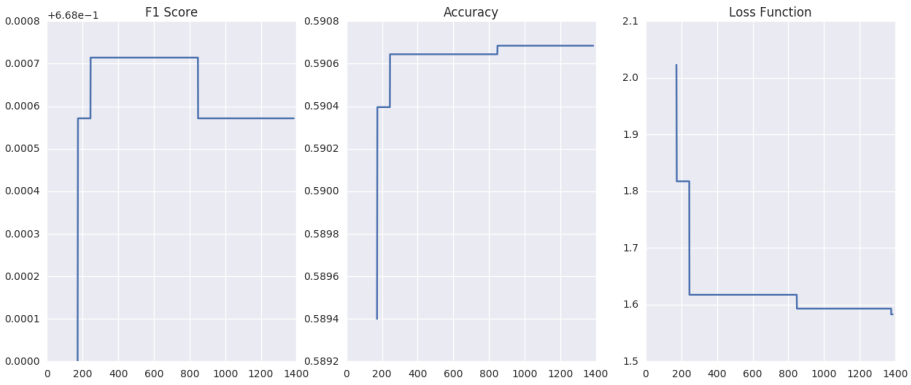


Figure 7: Training via Random Local Search

0.7.3 Learning via Gradient Descent

Please refer to notebook 7.03 Refinement - Learning via Gradient Descent.

As one might imagine there is actually a better for local optimization than a random step. We will improve upon our prediction by taking a step in the *optimal* direction at each learning phase. The loss function is the function that we are attempting to minimize. The gradient of this loss function will tell use the direction in which the loss function is most rapidly decreasing.

Consider our loss function in one-dimension (without regularization):

$$L_i = \sum_{j \neq y+i} \max(0, s_j - s_{y_i} + \Delta)$$

Where s_i is the score for our correct class and s_j is the score for incorrect class(es).

We obtain the gradient by differentiating with respect to the weights to obtain, for the row of the weight matrix corresponding to the correct class:

$$\nabla_{w_{y_i}} L_i = -\left(\sum_{j \neq y_i} \mathbb{1}(w_j^T x_i - w_{y_i}^T x_i + \Delta > 0) \right) x_i$$

and for the row(s) of the weight matrix corresponding to the incorrect class(es):

$$\nabla_{w_j} L_i = \mathbb{1}(w_j^T x_i - w_{y_i}^T x_i + \Delta > 0) x_i$$

Here $\mathbb{1}$ is the indicator function that is one if if the condition inside is true or zero otherwise.

0.7.3.1 Establish State of Training Session

```
>>> training_set, test_set = pull_training_and_test_sets(limit=700000,split=.99)
>>> features, outcomes = pull_and_shape_batch(action_ids=test_set)
>>> initialize_training_session()
>>> batch_size = 500
>>> for i in range(int(len(training_set)/batch_size)):
>>>     Q.enqueue(train_via_gradient_descent,
>>>               action_ids=training_set[i*batch_size:(i+1)*batch_size],
>>>               gamma=0.001)
>>> counts, f_1_scores, \
>>>     accuracies, \
```

```
>>>     loss_values = prepare_plot_vectors(features,
>>>                                        outcomes,
>>>                                        length=int(len(training_set)/batch_size))
```

0.7.3.2 Assess Results

This method, using a batch size of 50 and 700000 samples yielded

- Accuracy: 0.797441
- F1 Score: 0.782857

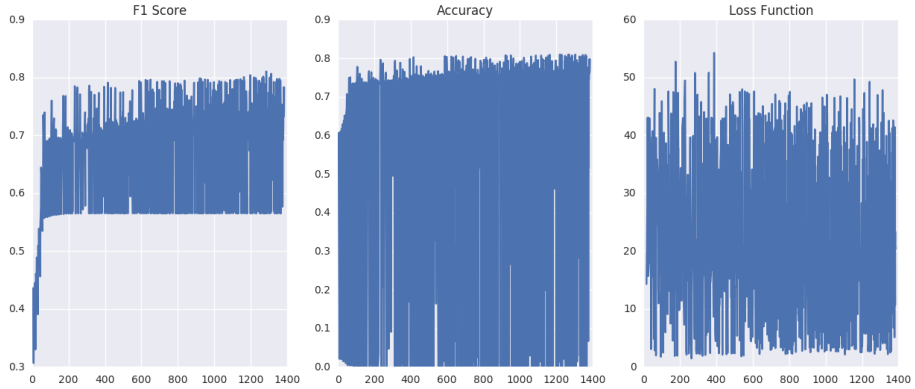


Figure 8: Training via Gradient Descent

0.7.4 Learning through a multi-layer Neural Network

At this point, we hit a wall. The complexity of managing the state of our learner via a Redis learner and the processing of learning jobs via a distributed network of python servers proved to be insurmountable at this time. The implementation of a multi-layer neural network requires considerable investment in our system architecture that is not feasible at this time.

0.7.5 Learning via Random Search followed by Random Local Search

0.7.5.1 Assess Results

This method, using a batch size of 50 and 700000 samples yielded

- Accuracy: 0.756756
- F1 Score: 0.786571

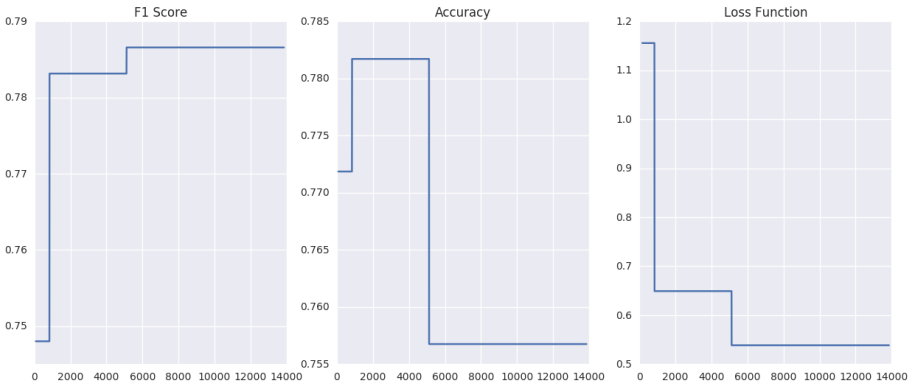


Figure 9: Training via Random Search

- Accuracy: 0.756475
- F1 Score: 0.786429

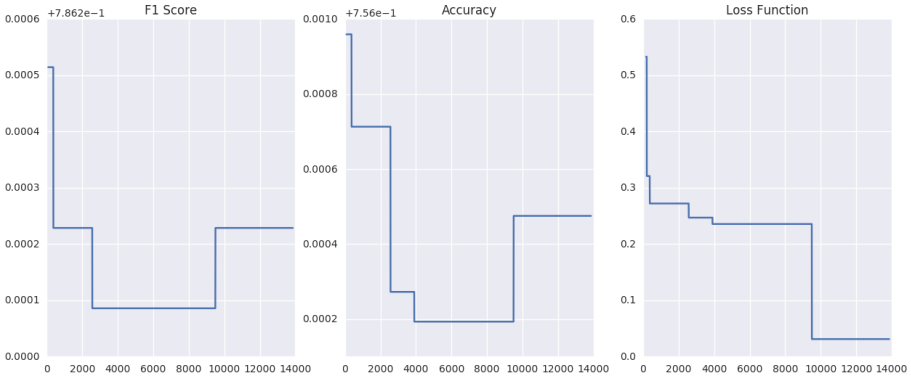


Figure 10: Training via Random Local Search

0.7.6 Learning via Random Search followed by Gradient Descent

0.7.6.1 Assess Results

This method, using a batch size of 50 and 700000 samples yielded

- Accuracy: 0.702685
- F1 Score: 0.739000

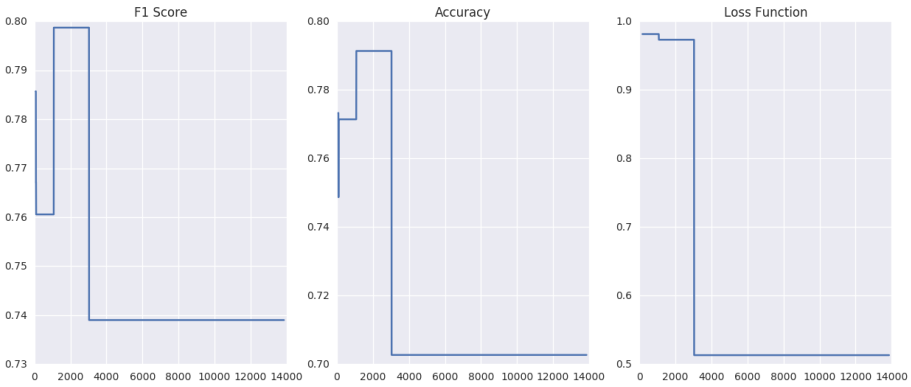


Figure 11: Training via Random Search

- Accuracy: 0.702975
- F1 Score: 0.739000

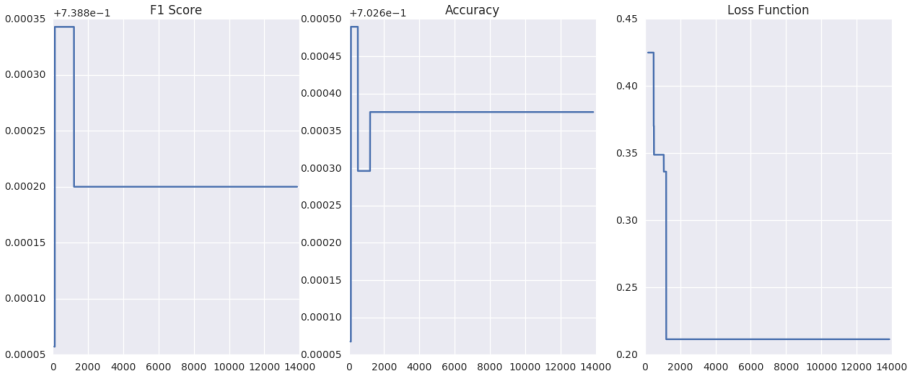


Figure 12: Training via Random Local Search

0.7.7 Learning via Gradient Descent in Multiple Epochs

0.7.7.1 Assess Results

This method, using a batch size of 500 and 700000 samples trained in five epochs yielded

- Accuracy: 0.828243
- F1 Score: 0.824857

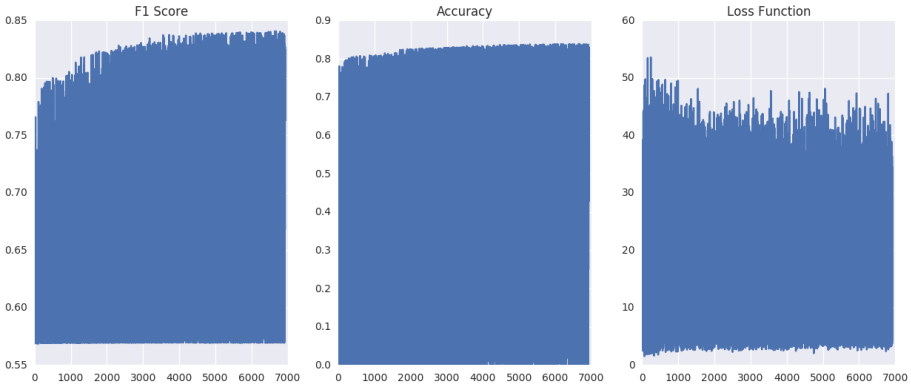


Figure 13: Training via Random Search

0.8 Results

0.8.1 Summary of Results

method	Accuracy	F1 Score
Random Search	0.803451	0.810321
Random Local Search	0.590684	0.668573
Gradient Descent	0.797441	0.782857
Random Search	0.756756	0.786571
Random Search, Random Local Search	0.756475	0.786429
Random Search	0.702685	0.739000
Random Search, Gradient Descent	0.702975	0.739000
Gradient Descent, Five Epochs	0.828243	0.824857

Until we ran stochastic gradient descent in multiple epochs, our best performance was the original random search. In running several different methods for training, we note that a single epoch gradient descent performed quite well.

We then hit upon the idea of using stochastic gradient descent over multiple

epochs. We ran over five epochs and hit upon our best results.

0.8.2 Final Model

As a final model, we recommend using the Gradient Descent learner over multiple epochs. We note that our system is actually performing stochastic gradient descent. We used batch sizes of both 50 and 500. This process can actually be run considerably more times and we would expect to see better results. A next step in this experimental process would be to see at what point the process can no longer be improved upon.

A brief note on our reinforcement learning approach to this task. We note that the accuracy and f1 score metrics are not used in training the learner at all. They are used as external metrics to independently assess the progress of our learner. It is the loss function that is used in the training of the learner and the loss function is never exposed to the test data. We can therefore, reasonably expect that the accuracy and f1 scores would generalize to new data.

0.8.3 Benchmark Comparison

We set out to achieve a benchmark of an accuracy of 0.8. We achieved this via our random learner, though subsequent random tests did not perform as well. Our Gradient Descent model very nearly achieved this.

0.9 Conclusion

0.9.1 Summary of Project

This project allowed me to develop many tools that I will use again. Perhaps the greatest success of this project is the portability of data provided by the `docker-compose` tool in conjunction with the Postgres native docker image. In my past work, the data itself has been the least portable aspect of the project, and using this tool I have been able to run this project on no less than four different systems. This has allowed my great flexibility in trying different hardware configurations. This will prove instrumental in developing pipelines for solving additional kaggle tasks in the future.

Additionally, the `rq` worker system has been a tremendous success. When I first conceived of this idea, using delayed job processing as a means of accessing multiple cores on a single cpu or in the interest of doing work across a cluster, I was not certain that it would work. Not only did it work, it has given me many ideas upon which I can iterate going forward.

Building the various learners by hand gave me great insight into the math underlying a perceptron learner and a network of perceptron learners. While I doubt I will ever use this code again, I learned a great deal in the implementation and am better algorithmist as well as programmer for having done this work.

In building our learner, we iterated through several phases: pure randomness, local randomness, stochastic gradient descent and neural networks. It was very illuminating to see the results take shape at each new phase.

In terms of what didn't work, the worker system is limited in what it can do. It can not distribute the multiplication of a single matrix across many cores. In this sense, I haven't really dealt with a core multi-threading problem. I think in the future, I will look into the Blaze ecosystem. This is a library that is being developed by Continuum Analytics. I think here I shall stand on the shoulders of giants.

In terms of the learners, we did not see amazing results. A lot of this has to do with just biting off an enormous data set at the same time as I was trying to write my own libraries from scratch. I think that had I chosen to use an open-source library designed to work on large data sets, such as TensorFlow, we would have seen much greater results.

Lastly, I was never able to get the cluster to work correctly. I think that the Docker Swarm technology I have been attempting to leverage is not quite ready and is too much in a beta state. I literally say the technology change while I was working on the project and my early code would no longer run. I think I would like to implement a more stable solution to clustering such as the Kubernetes library.

0.9.2 Steps for Improvment

I think we can look at three main ways to improve this project. All three have to do with looking to outside libraries.

1. I do not need to reinvent high performance computing, especially given the fact that I have no viable solution for distributed matrix computations. The solution to this is use Dask, part of the Blaze ecosystem.
2. Docker Swarm is not ready for prime time. Use Kubernetes for clustering. It is robust and fully supported.
3. Writing code from scratch is a worthwhile exercise and an excellent cap to program, but next time use TensorFlow.

0.9.3 Reflection

It is important to note that nearly very line of code in this project was written by me. In this sense, there has been great value in attempting to implement

some of the most challenging machine learning concepts from scratch. That said, it is clearly not the best solution to this task. Tensorflow or a similar library should have been brought to bear on this task. It is of note that tensorflow has been developed by a team of more than 20 people. While I have learned a lot in writing this code base, especially in terms of writing clean Python, perhaps the most important thing I have learned is that it is okay to stand on the shoulders of giants. I don't need to do everything from scratch.

This project attempted to tackle quite a bit. I was attempting to engineer a robust system that could handle a large data set. In the end, my decision to hand code everything as opposed to using libraries gave access to high performance that I might not have had otherwise, but in spending time on the engineering, I never quite got to a point where I was iterating on the algorithms themselves.