Binary Classifcaton via a Reinforcement Learner

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Abstract

The purpose of this project is to solve a Kaggle competition using neural networks of varying complexities. The competition in question is sponsored by Red Hat. Given situational (an "action" data set) and customer (a "people" data set) information, the goal is to predict customer behavior for a given action. This project will use these two data sources and neural network/reinforcement learning techniques to prepare an algorithm capable of predicting outcomes against a third situational (a "test action" data set) source. The infrastructure designed and built for this project is informed by and informs the work Docker & Jupyter. This work is accompanied by a set of Jupyter notebooks and a docker-compose.yml file that can be run in order to validate all information here presented. **LINK**.

Contents

Chapter 1

Definition

Please refer to notebook `1 Definition`.

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 $0, 1$.

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."

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. Pull a batch of One-Hot Encoded vectors from the `action` table to pass to a Reinforcement Learner
4. Create, Update, and Store the parameters of the Reinforcement Learner
5. Use the Reinforcement Learner to run a set of predictions on Test Data.
6. Assess the accuracy of these predictions

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.

1.3 Metrics

The quality of a solution to this task will be measured using the following test error metric

$$\text{Ave}(I(y_i \neq \hat{y}_i))$$

Here, I is an indicator function which yields 0 if the predicted outcome ($\hat{y}_i$) matches the actual outcome (y_i). While the size of the dataset (over 2 million rows in the action set) makes this problem atypical, it is at the end of the day, a binary classifcation problem. As such this simple metric is sufficient to measure our accuracy.

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.

TODO: Learner Assessment Diagram

1.3.1 Solution Format

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
```

Chapter 2

Preliminary Data Analysis

2.1 Connecting to PostgreSQL

Use notebook `2.01 Connecting to PostgreSQL`.

We store all included data in a PostgreSQL database. By and large, we access this database using the psycopg2 library.

```
import psycopg2

from os import environ
conn = psycopg2.connect(dbname='postgres',
                        user='postgres',
                        host=environ['POSTGRES_1_PORT_5432_TCP_ADDR'])
cur = conn.cursor()

cur.execute("SELECT COUNT(*) FROM people"); print(cur.fetchone())
cur.execute("SELECT COUNT(*) FROM action"); print(cur.fetchone())
```

```
(189118,)
(2695978,)
```

```
conn.close()
```

TODO: Diagram just Jupyter and DB

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. prepare sql initialization scripts
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

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. It is of note, that we have also added our `one_hot_ppl_act` table which will contain one-hot encoded data created by joining our two tables, however, this will be discussed later. The full structure can be viewed in the seeding file here. This functionality is part of the PostgreSQL public Docker image.

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.

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   |
```

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)
```

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)
```

2.5 Define the Basic Structure

TODO: Jupyter File

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.

2.5.1 Number of Rows in database tables

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

2.5.2 Number of Columns per Data Type

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

2.6 Identify Unique Labels

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.

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.

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)
```

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.

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.

2.10 Create Histograms of Data

Finally, we use the Python library seaborn to create plots of our data as histograms.

First, we import the necessary libraries, then instantiate a connection to our database.

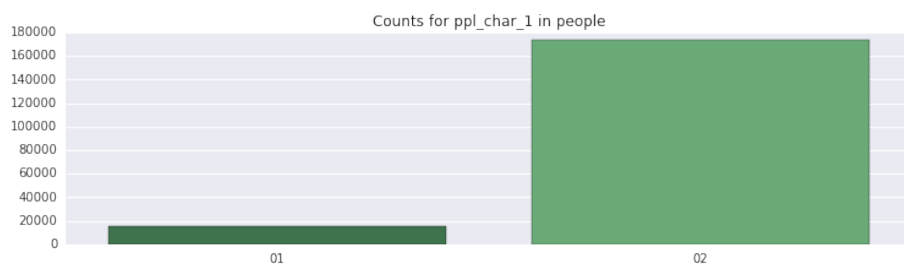
```
import psycopg2
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

from os import environ
conn = psycopg2.connect(dbname='postgres',
                        user='postgres',
                        host=environ['POSTGRES_1_PORT_5432_TCP_ADDR'])
cur = conn.cursor()
```

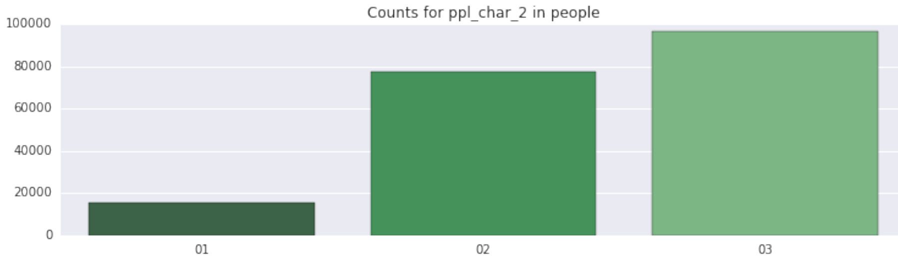
Next, we define a function that we will use to create numbered bins four distinct labels for each column.

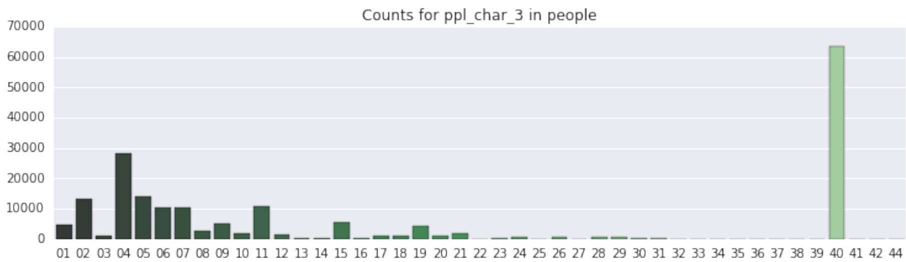
```
column = 'ppl_char_1'
def hist_buckets(column, table, cur):
    sql = "SELECT DISTINCT {} FROM {};".format(column,table)
    cur.execute(sql)

    labels = [str(l[0]) for l in cur.fetchall()]
    labels.sort()
    sql = "SELECT {} FROM ".format(','.join(labels).replace(' ','_'))
    sql_rows = ["""(SELECT COUNT({})
                    FROM {}
                    WHERE {} = '{}') as {}""".format(column,
                                                     table,
                                                     column,
                                                     label,
                                                     label.replace(' ','_'))

                                                     for label in labels]

    sql += ",".join(sql_rows)

    cur.execute(sql)
    bins = cur.fetchall()[0]
    bins = [int(bn.replace('(','').replace(')','')) for bn in bins]
    return bins, labels
```

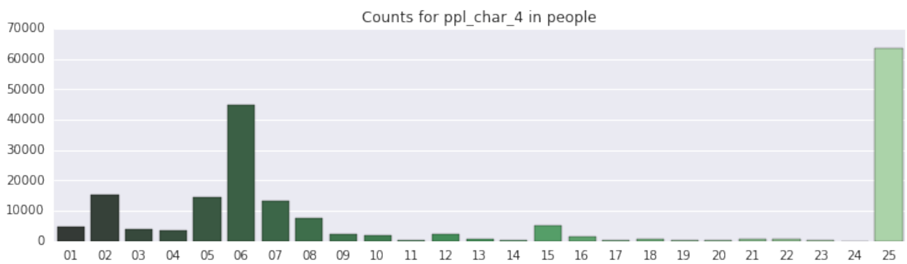
Then, we define a function to create our bar plot. We are using the `seaborn` library which is designed to create beautiful plots with minimal configuration.

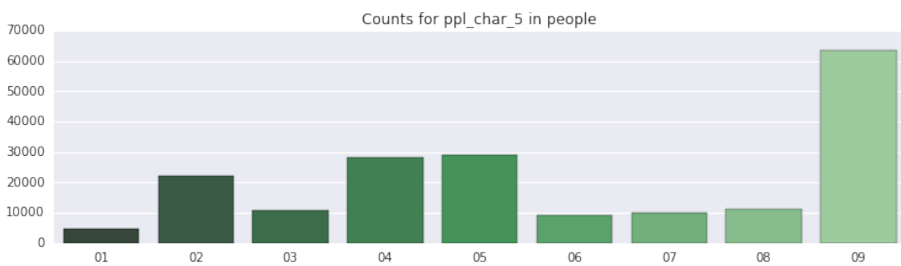
```
def bar_plot(col,table,cur):
    vals,labels = hist_buckets(col,table,cur)
    x = np.arange(len(vals))
    y = np.array(vals)
    f = plt.figure(figsize=(12,3))
    ax = f.add_axes([0.1, 0.1, 0.8, 0.8])
    sns.barplot(x=x, y=y,palette='Greens_d')
    ax.set_title("Counts for {} in {}".format(col,table))
    ax.set_xticks(x)
    ax.set_xticklabels([label.replace('type ','') for label in labels])

bar_plot('ppl_char_1','people',cur)
bar_plot('ppl_char_2','people',cur)
bar_plot('ppl_char_3','people',cur)
bar_plot('ppl_char_4','people',cur)
bar_plot('ppl_char_5','people',cur)
bar_plot('ppl_char_6','people',cur)
bar_plot('ppl_char_7','people',cur)
bar_plot('ppl_char_8','people',cur)
bar_plot('ppl_char_9','people',cur)
bar_plot('act_char_1','action',cur)
bar_plot('act_char_2','action',cur)
bar_plot('act_char_3','action',cur)
bar_plot('act_char_4','action',cur)
bar_plot('act_char_5','action',cur)
bar_plot('act_char_6','action',cur)
bar_plot('act_char_7','action',cur)
bar_plot('act_char_8','action',cur)
bar_plot('act_char_9','action',cur)
```

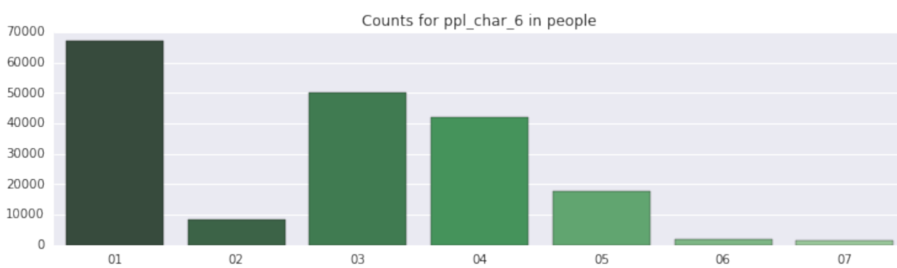


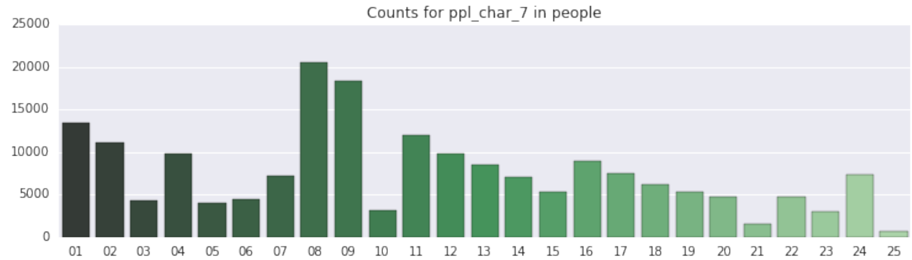

Counts for ppl_char_2 in people
100000
80000
60000
40000
20000
0
01
02
03

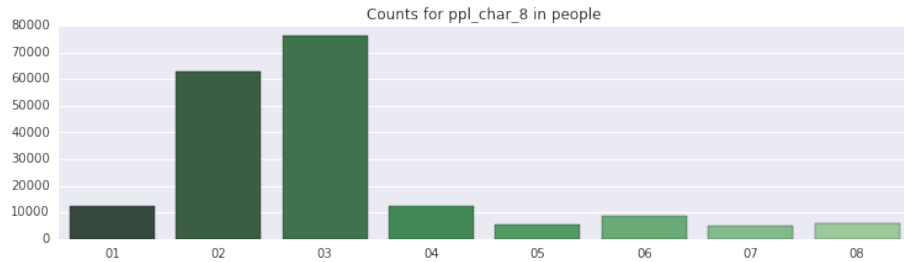

Counts for ppl_char_3 in people
70000
60000
50000
40000
30000
20000
10000
0
01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 44

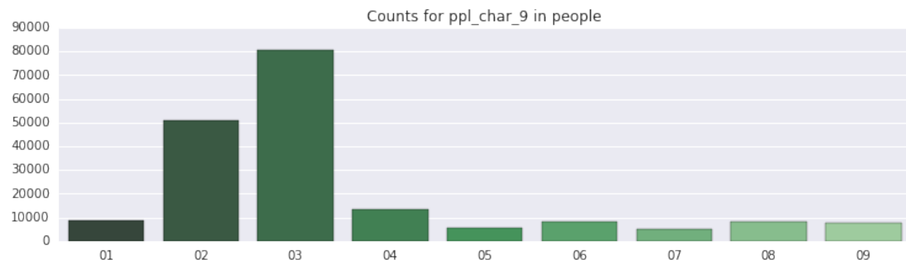

Counts for ppl_char_4 in people
70000
60000
50000
40000
30000
20000
10000
0
01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25

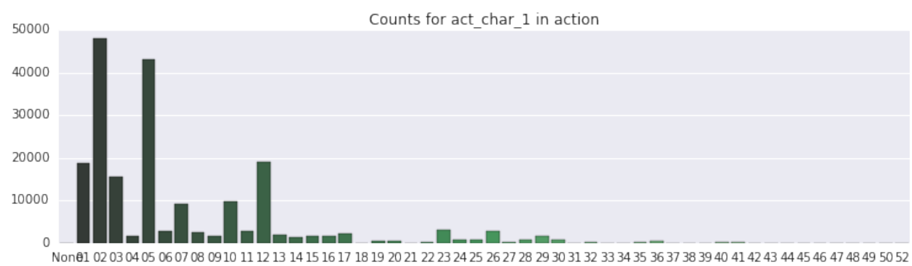

Counts for ppl_char_5 in people
70000
60000
50000
40000
30000
20000
10000
0
01 02 03 04 05 06 07 08 09

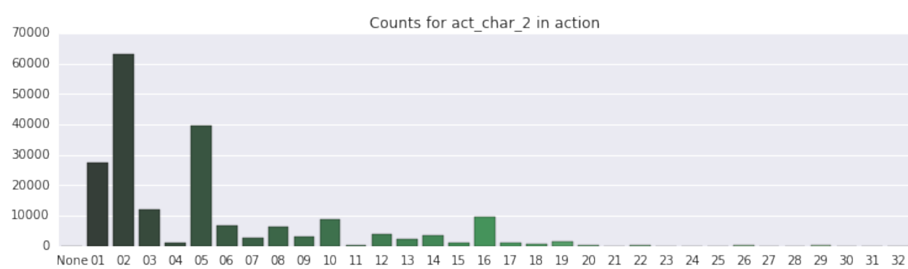

Counts for ppl_char_6 in people
70000
60000
50000
40000
30000
20000
10000
0
01 02 03 04 05 06 07

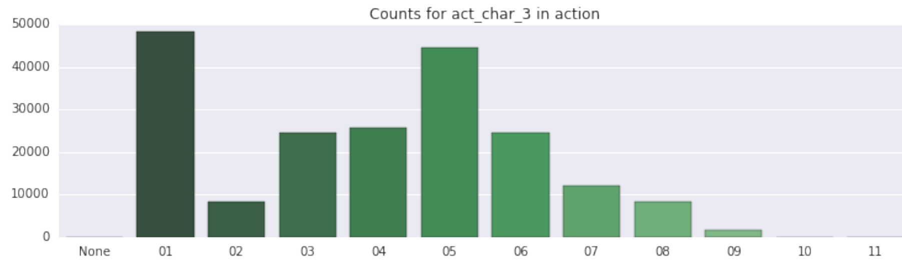

Counts for ppl_char_7 in people
25000
20000
15000
10000
5000
0
01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25

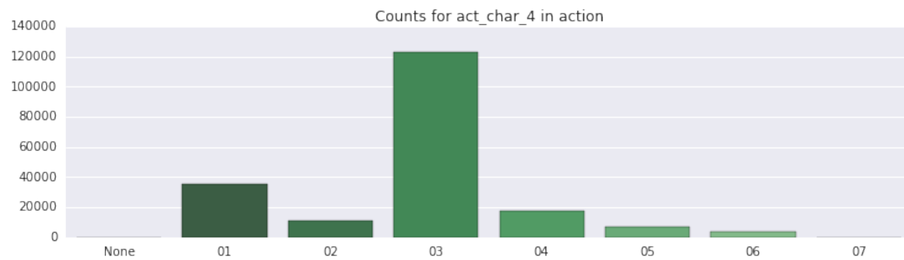

Counts for ppl_char_8 in people
80000
70000
60000
50000
40000
30000
20000
10000
0
01 02 03 04 05 06 07 08

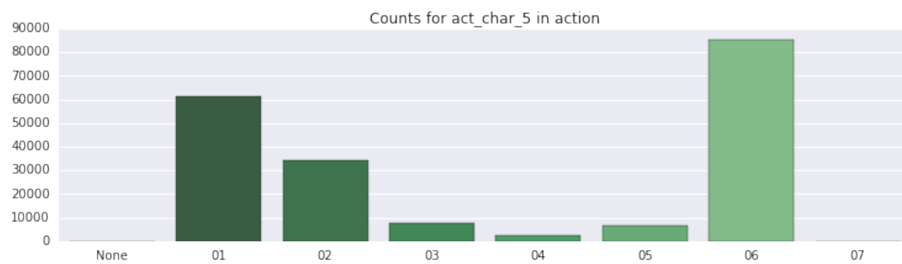

Counts for ppl_char_9 in people
90000
80000
70000
60000
50000
40000
30000
20000
10000
0
01 02 03 04 05 06 07 08 09

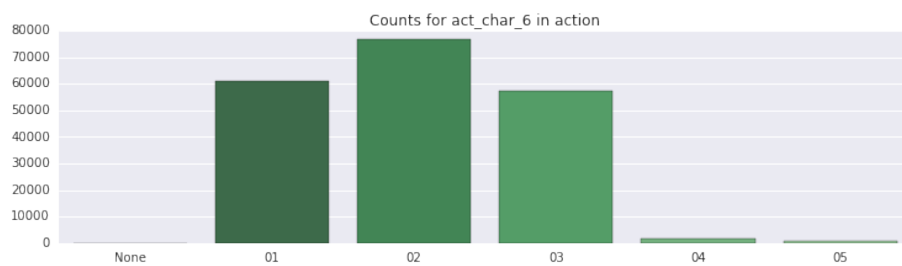

Counts for act_char_1 in action
50000
40000
30000
20000
10000
0
None 01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 52

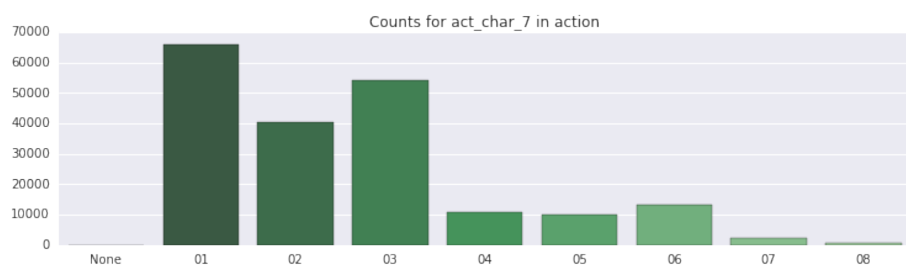

Counts for act_char_2 in action
70000
60000
50000
40000
30000
20000
10000
0
None 01 02 03 04 05 06 07 08 09 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32

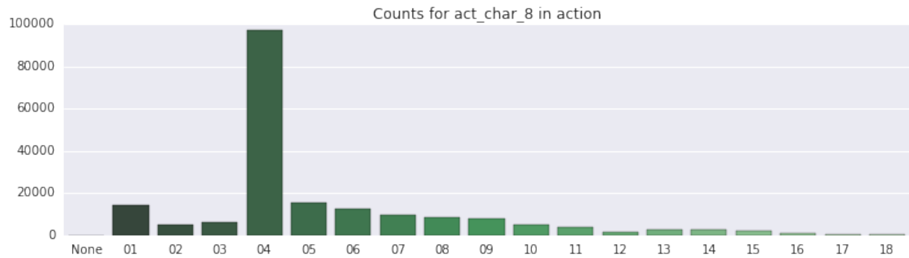

Counts for act_char_3 in action
50000
40000
30000
20000
10000
0
None 01 02 03 04 05 06 07 08 09 10 11


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


Counts for act_char_8 in action
100000
80000
60000
40000
20000
0
None
01
02
03
04
05
06
07
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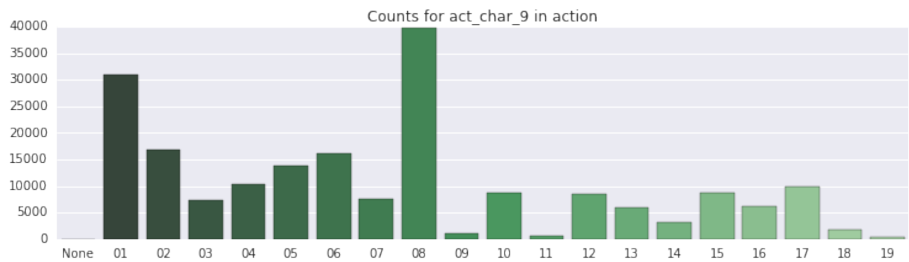
14
15
16
17
18


Counts for act_char_9 in action
40000
35000
30000
25000
20000
15000
10000
5000
0
None
01
02
03
04
05
06
07
08
09
10
11
12
13
14
15
16
17
18
19

Chapter 3

Algorithms and Techniques

3.1 One-Hot Encoding

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.

3.1.1 One-Hot Encoding Example

```
import psycopg2
import numpy as np
from os import environ
conn = psycopg2.connect(dbname='postgres',
                        user='postgres',
                        host=environ['POSTGRES_1_PORT_5432_TCP_ADDR'])
cur = conn.cursor()

 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.

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.

3.2.1 Score Function

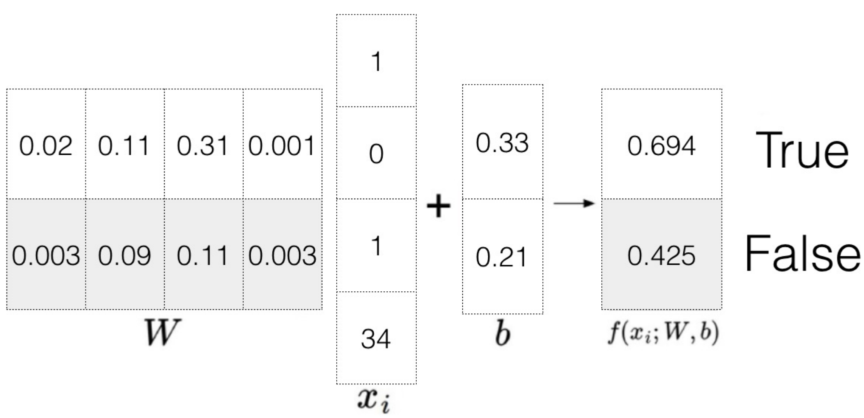
We will develop a score function that maps input vectors to class scores

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

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.



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.

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.

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.

3.3 Optimization

3.4 Benchmark

The quality of a solution to this task will be measured using the following test error metric

$$\text{Ave}(I(y_i \neq \hat{y}_i))$$

Here, I is an indicator function which yields 0 if the predicted outcome ($\hat{y}_i$) matches the actual outcome (y_i). While the size of the dataset (over 2 million rows in the action set) makes this problem atypical, it is at the end of the day, a binary classification problem. As such this simple metric is sufficient to measure our accuracy.

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.

Chapter 4

Exploratory Visualization

4.1 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.

In this section, you will need to provide some form of visualization that summarizes or extracts a relevant characteristic or feature about the data. The visualization should adequately support the data being used. Discuss why this visualization was chosen and how it is relevant. Questions to ask yourself when writing this section:

- *Have you visualized a relevant characteristic or feature about the dataset or input data?*
- *Is the visualization thoroughly analyzed and discussed?*
- *If a plot is provided, are the axes, title, and datum clearly defined?*

Chapter 5

Data Preprocessing

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.

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
```

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
```

5.1.3 All Sets

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

```
$ 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:

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`. Here is a minimal implementation of this.

```
import psycopg2
import numpy as np
from os import environ
conn = psycopg2.connect(dbname='postgres',
                        user='postgres',
                        host=environ['POSTGRES_1_PORT_5432_TCP_ADDR'])
cur = conn.cursor()

def update_one_hot_encoding(vector, action_id):
    sql = """
        UPDATE action
        SET act_one_hot_encoding = {}
        WHERE act_id='{}'
        """.format(psycopg2.Binary(vector), action_id)
    cur.execute(sql)
    conn.commit()

eye_3 = np.eye(3)

update_one_hot_encoding(conn, cur, eye_4, action_id)
```

Next, we verify that the vector was properly stored.

```
def fetch_one_hot_encoding(conn, cur, action_id):
    sql = """
        SELECT act_one_hot_encoding
        FROM action
        WHERE act_id='{}'
        """.format(action_id)
```

```
    cur.execute(sql)
    buf = cur.fetchone()[0]
    return np.frombuffer(buf)
```

```
fetch_one_hot_encoding(conn, cur, action_id)
array([ 1.,  0.,  0.,  0.,  1.,  0.,  0.,  0.,  1.])
```

Chapter 6

Implementation

In this section, the process for which metrics, algorithms, and techniques that you implemented for the given data will need to be clearly documented. It should be abundantly clear how the implementation was carried out, and discussion should be made regarding any complications that occurred during this process. Questions to ask yourself when writing this section: - *Is it made clear how the algorithms and techniques were implemented with the given datasets or input data?* - *Were there any complications with the original metrics or techniques that required changing prior to acquiring a solution?* - *Was there any part of the coding process (e.g., writing complicated functions) that should be documented?*

Chapter 7

Refinement

In this section, you will need to discuss the process of improvement you made upon the algorithms and techniques you used in your implementation. For example, adjusting parameters for certain models to acquire improved solutions would fall under the refinement category. Your initial and final solutions should be reported, as well as any significant intermediate results as necessary. Questions to ask yourself when writing this section: - *Has an initial solution been found and clearly reported?* - *Is the process of improvement clearly documented, such as what techniques were used?* - *Are intermediate and final solutions clearly reported as the process is improved?*

Chapter 8

Results

(approx. 2-3 pages)

8.1 Model Evaluation and Validation

In this section, the final model and any supporting qualities should be evaluated in detail. It should be clear how the final model was derived and why this model was chosen. In addition, some type of analysis should be used to validate the robustness of this model and its solution, such as manipulating the input data or environment to see how the model's solution is affected (this is called sensitivity analysis). Questions to ask yourself when writing this section: - *Is the final model reasonable and aligning with solution expectations? Are the final parameters of the model appropriate?* - *Has the final model been tested with various inputs to evaluate whether the model generalizes well to unseen data?* - *Is the model robust enough for the problem? Do small perturbations (changes) in training data or the input space greatly affect the results?* - *Can results found from the model be trusted?*

8.2 Justification

In this section, your model's final solution and its results should be compared to the benchmark you established earlier in the project using some type of statistical analysis. You should also justify whether these results and the solution are significant enough to have solved the problem posed in the project. Questions to ask yourself when writing this section: - *Are the final results found stronger than the benchmark result reported earlier?* - *Have you thoroughly analyzed and discussed the final solution?* - *Is the final solution significant enough to have solved the problem?*

Chapter 9

Conclusion

(approx. 1-2 pages)

9.1 Free-Form Visualization

In this section, you will need to provide some form of visualization that emphasizes an important quality about the project. It is much more free-form, but should reasonably support a significant result or characteristic about the problem that you want to discuss. Questions to ask yourself when writing this section: - *Have you visualized a relevant or important quality about the problem, dataset, input data, or results?* - *Is the visualization thoroughly analyzed and discussed?* - *If a plot is provided, are the axes, title, and datum clearly defined?*

9.2 Reflection

In this section, you will summarize the entire end-to-end problem solution and discuss one or two particular aspects of the project you found interesting or difficult. You are expected to reflect on the project as a whole to show that you have a firm understanding of the entire process employed in your work. Questions to ask yourself when writing this section: - *Have you thoroughly summarized the entire process you used for this project?* - *Were there any interesting aspects of the project?* - *Were there any difficult aspects of the project?* - *Does the final model and solution fit your expectations for the problem, and should it be used in a general setting to solve these types of problems?*

9.3 Improvement

In this section, you will need to provide discussion as to how one aspect of the implementation you designed could be improved. As an example, consider ways your implementation can be made more general, and what would need to be modified. You do not need to make this improvement, but the potential solutions resulting from these changes are considered and compared/contrasted to your current solution. Questions to ask yourself when writing this section: - *Are there further improvements that could be made on the algorithms or techniques you used in this project? - Were there algorithms or techniques you researched that you did not know how to implement, but would consider using if you knew how? - If you used your final solution as the new benchmark, do you think an even better solution exists?*

Before submitting, ask yourself. . .

- Does the project report you've written follow a well-organized structure similar to that of the project template?
- Is each section (particularly **Analysis** and **Methodology**) written in a clear, concise and specific fashion? Are there any ambiguous terms or phrases that need clarification?
- Would the intended audience of your project be able to understand your analysis, methods, and results?
- Have you properly proof-read your project report to assure there are minimal grammatical and spelling mistakes?
- Are all the resources used for this project correctly cited and referenced?
- Is the code that implements your solution easily readable and properly commented?
- Does the code execute without error and produce results similar to those reported?

9.4 Appendix

<a ## `Dockerfile`

```
 docker/postgres/Dockerfile
FROM postgres
COPY tables.sql /docker-entrypoint-initdb.d/tables.sql
COPY act_test.csv /docker-entrypoint-init.d/act_test.csv
COPY act_train.csv /docker-entrypoint-init.d/act_train.csv
COPY people.
csv /docker-entrypoint-init.d/people.csv
```

9.4.1