



**HAL**  
open science

# Applying Deep Machine Learning for psycho-demographic profiling of Internet users using O.C.E.A.N. model of personality

Iaroslav Omelianenko

► **To cite this version:**

Iaroslav Omelianenko. Applying Deep Machine Learning for psycho-demographic profiling of Internet users using O.C.E.A.N. model of personality. [Research Report] NewGround LLC. 2017. hal-01482770v1

**HAL Id: hal-01482770**

**<https://hal.science/hal-01482770v1>**

Submitted on 3 Mar 2017 (v1), last revised 5 Jul 2017 (v2)

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons CC0 - Public Domain Dedication 4.0 International License

# Applying Deep Machine Learning for psycho-demographic profiling of Internet users using O.C.E.A.N. model of personality

IAROSLAV OMELIANENKO

Research Director, NewGround LLC

yaric@newground.com.ua

March 3, 2017

## Abstract

*In the modern era, each Internet user leaves enormous amounts of auxiliary digital residuals (footprints) by using a variety of on-line services. All this data is already collected and stored for many years. In recent works, it was demonstrated that it's possible to apply simple machine learning methods to analyze collected digital footprints and to create psychological profiles of individuals. However, while these works clearly demonstrated the applicability of machine learning methods for such an analysis, created simple prediction models still lacks accuracy necessary to be successfully applied to practical needs. We have assumed that using advanced deep machine learning methods may considerably increase the accuracy of predictions. We started with simple machine learning methods to estimate basic prediction performance and moved further by applying advanced methods based on shallow and deep neural networks. Then we compared prediction power of studied models and made conclusions about its performance. Finally, we made hypotheses how prediction accuracy can be further improved. As result of this work, we provide full source code used in the experiments for all interested researchers and practitioners in corresponding GitHub repository. We believe that applying deep machine learning for psychological profiling may have an enormous impact on the society (for good or worse) and providing full source code of our research we hope to intensify further research by the wider circle of scholars.*

## 1. INTRODUCTION

By using various on-line services, modern Internet user leaves an enormous amount of digital tracks in the form of server logs, user-generated content, etc. All these information bits meticulously saved by on-line service providers create the vast amount of digital footprints for every Internet user. In recent research [Lambiotte, R., and Kosinski, M., 2014], it was demonstrated that by applying simple machine learning methods it's possible to find statistical correlations between digital footprints and psycho-demographic profile of individuals. The considered psycho-demographic profile comprise of psychometric scores based on five-factor O.C.E.A.N. model of personality [Goldberg et. al, 2006] and demographic scores such as Age, Gender and the Political Views. The O.C.E.A.N. is an abbreviation for *Openness, Conscientiousness, Extroversion, Agreeableness, and Neuroticism*.

In this work we decided to test whether applying advanced machine learning methods to analyze digital footprints of Internet users has enough predictive performance to create precise psycho-demographics profiles of personality. For our experiments we used data corpus comprising of psycho-demographic scores of individuals and their digital footprints in form of Facebook likes. The data corpus kindly provided by M. Kosinski through corresponding web site: <http://dataminingtutorial.com>.

We started our experiments with building simple machine learning models based on linear/logistic regression methods as proposed by M. Kosinski in [Kosinski et. al, 2016]. By training and execution of simple models we estimated basic predictive performance of machine learning methods against available data set. Then we proceeded with experiments against advanced machine learning methods based on shallow and deep neural networks.

The full source code of our experiments provided in form of GitHub repository: <https://github.com/NewGround-LLC/psistats>

The source code is written in R programming language [R Core Team, 2015] which is highly optimized for statistical data processing and allows to apply advanced deep machine learning algorithms by bridging with Google Brain's TensorFlow framework [Google Brain Team, 2015].

This paper is organized as follows: In Section 2, we describe data corpus, and its preprocessing routines. It is followed in Section 3 by details about how to build and run simple prediction models based on linear and logistic regression with results of their execution. In Section 4, we provide measures to create and execute advanced prediction models based on artificial neural networks. Finally, in Section 6 we compare the performance of different machine learning methods studied in this work and draw conclusions about the predictive power of models build with considered architectures.

## 2. DATA CORPUS PREPARATION

In this section, we consider the creation of input data corpus from the publicly available data set, and its pre-processing it to simplify further analysis by machine learning algorithms.

### 2.1. Data Set Description

The data set kindly provided by M. Kosinski and used in this work contains psycho-demographic profiles of  $n_u = 110728$  Facebook users and  $n_L = 1580284$  of associated Facebook likes. For simplicity and manageability, the sample is limited to U.S. users [Kosinski et. al, 2016]. The following three files can be downloaded:

1. *users.csv*: contains psycho-demographic user profiles. It has  $n_u = 110728$  rows (excluding the row holding column names) and nine columns: anonymised user ID, gender ("0" for male and "1" for female), age, political views ("0" for Democrat and "1" for Republican), and scores of five-factor model of personality [Goldberg et. al, 2006].
2. *likes.csv*: contains anonymized IDs and names of  $n_L = 1580284$  Facebook Likes. It has two columns: ID and name.
3. *users-likes.csv*: contains the associations between users and their Likes, stored as user-Like pairs. It has  $nu_L = 10612326$  rows and two columns: user ID and Like ID. An existence of a user-Like pair implies that a given user had the corresponding Like on their profile.

### 2.2. Data pre-processing

It is an important step in machine learning analysis which will significantly reduce the time needed for analysis and result in better prediction power of created machine learning models.

First, we created *sparse matrix* representing relations among users and their Facebook likes. This matrix has an enormous number of feature dimensions: 10612326 of features columns representing the users-likes relation. Thus after construction, we applied data trimming of rare data points and performed dimensionality reduction using singular value decomposition (SVD) [Golub, G. H., and Reinsch, C. 1970].

The necessary pre-processing steps may be summarized as followed:

1. Construction of sparse users-likes matrix, which presents *many-to-many* relationships between users and their digital footprints in the form of collected Facebook likes. The constructed matrix is enormous with high sparsity, so it is appropriate to operate with it and store it in *sparse data format*, which optimized for such kind of data.
2. Trimming of sparse users-likes matrix to exclude rare data points which have minuscule significance
3. Data imputation for missed values
4. Dimensionality reduction to reduce enormous number of features in the generated data corpus by applying *singular value decomposition* (SVD)
5. The *factor rotation analysis* to simplify obtained scores over SVD dimensions after dimensionality reduction

### Construction of sparse users-likes matrix and matrix trimming

Before analysis, we build from provided comma-separated files the *sparse* matrix with users-likes relationships encoded. After that, the sparse matrix was *trimmed* by removing rare data points. As a result, the significantly reduced data corpus was created, imposing lower demands on computational resources and more useful for manual analysis to extract specific patterns. The descriptive statistics of users-likes matrix before and after trimming present in Table 1.

Descriptive statistics	Raw Matrix	Trimmed Matrix
# of users	110 728	19 742
# of unique Likes	1 580 284	8 523
# of User-Like pairs	10 612 326	3 817 840
Matrix density	0,006%	2,269%
Likes per User		
Mean	96	193
Median	22	106
Minimum	1	50
Maximum	7 973	2 487
Users per Like		
Mean	7	448
Median	1	290
Minimum	1	150
Maximum	19 998	8 445

**Table 1:** The descriptive statistics of raw and trimmed users-likes matrix with minimum users per like threshold set to  $u_L = 150$  and minimum likes per user  $L_u = 50$

The users-likes matrix can be constructed from provided three comma-separated files with the help of accompanying script written in R language: *src/preprocessing.R*. To use this script make sure that **input\_data\_dir** variable in the *src/config.R* points to the root directory where sample data corpus in the form of .CSV files were unpacked.

To start pre-processing and trimming, run the following command from terminal in the project's root directory:

```
$Rscript ./src/preprocessing.R -u 150 -l 50
```

where: **-u** is the minimum number of users per like  $u_L$ , and **-l** is the minimum number of likes per user  $L_u$  to keep in resulting matrix.

The values for the minimum number of users per like  $u_L$  and the minimum number of likes per user  $L_u$  was selected based on [Kosinski et. al, 2016]. We have experimented with other set parameters as well ( $u_L = 20$  and  $L_u = 2$ ), but accuracy of trained prediction models degraded.

### Data imputation of missed values

The raw data corpus has missed values in column with 'Political' *dependent variable* data. Before building the prediction model for this dependent variable, it is advisable to impute missed values. In this work, we will apply multivariate imputation to fill missed values [van Buuren, Groothuis-Oudshoorn, 2011].

The data imputation performed by the same *src/preprocessing.R* script, as part of users-likes matrix building routine. The summary statistics for data imputation applied to *political* variable, presented in Table 2.

	est	se	t	df	Pr(>  t )	lo 95	hi 95	nmis	fmi	lambda
(Intercept)	1.39	0.01	102.29	1240.53	0.00	1.36	1.41	NA	0.06	0.05
gender	-0.02	0.01	-2.80	25.27	0.01	-0.04	-0.01	0	0.44	0.40
age	0.00	0.00	-0.73	577.61	0.47	0.00	0.00	0	0.09	0.08
ope	-0.23	0.00	-68.10	2446.16	0.00	-0.23	-0.22	0	0.04	0.04
con	0.05	0.00	10.92	20.28	0.00	0.04	0.06	0	0.49	0.44
ext	0.03	0.00	6.44	14.40	0.00	0.02	0.04	0	0.58	0.53
agr	0.02	0.00	6.72	189.32	0.00	0.02	0.03	0	0.15	0.14
neu	-0.01	0.00	-2.07	95.30	0.04	-0.02	0.00	0	0.22	0.20

**Table 2:** The descriptive statistics for data imputation applied to political variable using **LDA** method with number of multiple imputations equals to  $m = 5$ . The plausibility of applied multivariate imputation can be confirmed by low values in column **fmi** and **lambda**. The column **fmi** contains the fraction of missing information as defined in [Rubin DB, 1987], and the column **lambda** is the proportion of the total variance that is attributable to the missing data  $\lambda = \frac{B + \frac{B}{m}}{T}$ .

### Dimensionality reduction with SVD

After two previous steps, the resulting users-likes matrix still has a considerable number of features per data sample (8 523 of features columns). To make it more maintainable, we considered applying singular value decomposition [Golub, G. H., and Reinsch, C. 1970], representing eigendecomposition-based methods, projecting a set of data points into a set of dimensions. As it mentioned in [Kosinski et. al, 2016], reducing the dimensionality of data corpus has number of advantages:

- With reduced features space we can use fewer number of data samples, as it is required by most of the analysis algorithms that number of data samples exceeds the number of features (input variables)
- It will reduce risk of **overfitting** and increase statistical power of results
- It will remove **multicollinearity** and **redundancy** in data corpus by grouping related features (variables) in single dimension
- It will significantly reduce required computational power and memory requirements
- And finally it makes it easier to analyze data by hand over small set of dimensions as opposite to hundreds or thousands of separate features

To apply *SVD analysis* against generated users-likes matrix run the following command from project's root directory:

```
$Rscript ./src/svd_varimax.R --svd_dimensions 50 --apply_varimax true
```

where: `-svd_dimensions` is the number of *SVD dimensions* for projection, and `-apply_varimax` is the flag to indicate whether *varimax rotation* should be applied afterwards.

### Factor rotation analysis

The *factor rotation analysis* methods can be used to simplify *SVD dimensions* and increase their interpretability by mapping the original multidimensional space into a new, rotated space. Rotation approaches can be orthogonal (i.e., producing uncorrelated dimensions) or oblique (i.e., allowing for correlations between rotated dimensions).

We will apply one of the most popular orthogonal rotation - *varimax*. It minimizes both the number of dimensions related to each variable and the number of variables related to each dimension, thus improving the interpretability of the data.

For more details on rotation techniques, see [Abdi, H., 2003].

## 3. REGRESSION ANALYSIS

There is an abundance of methods developed to build prediction models based on large data sets. It's ranging from sophisticated methods such as Deep Machine Learning [Goodfellow et al., 2016], probabilistic graphical models [Daphne Koller, 2012], or support vector machines [Cortes & Vapnik, 1995], to much simpler, such as linear and logistic regressions [Yan, Su, 2009].

Starting with simple methods is common practice allowing the creation of good baseline prediction model with minimal computational efforts. The results obtained from these models can be used later to debug and estimate the quality of results obtained from advanced models.

### 3.1. Cross-Validation

In this work, we will apply *k-fold cross-validation* to help with avoiding model overfitting. In *k-fold cross-validation*, the original sample is randomly partitioned into  $k$  equal sized subsamples. Of the  $k$  subsamples, a single subsample is retained as the validation data for testing the model, and the remaining  $k - 1$  subsamples are used as training data. The cross-validation process is then repeated  $k$  times (the folds), with each of the  $k$  subsamples used exactly once as the validation data. The  $k$  results from the folds can then be averaged to produce a single estimation. The advantage of this method is that all observations are used for both training and validation, and each observation is used for validation exactly once. 10-fold cross-validation is commonly used, but in general,  $k$  remains an unfixed parameter [Kohavi, Ron, 1995].

### 3.2. Dimensionality Reduction

To reduce the number of features (input variables) in data corpus, we applied singular value decomposition (SVD) with subsequent varimax factor rotation analysis. The number of the varimax-rotated singular value decomposition dimensions ( $K$ ) has a considerable impact on the accuracy of model predictions. To find an optimal number of *SVD dimensions*, we performed analysis of relationships between  $K$  and accuracy of model predictions by producing series of regression models for different values of  $K$ . Then we plot prediction accuracy of created models against chosen number of  $K$  SVD dimensions. Typically the prediction accuracy grows rapidly within lower ranges of  $K$  and may start decreasing once the number of dimensions becomes large. Selecting a  $K$  that marks the end of a rapid growth

of prediction accuracy values usually offers decent interpretability of the topics. In general, the larger  $K$  values often provide better predictive power [Zhang, Marron, Shen, & Zhu, 2007]. See Figure 1 for results of our experiments.

To start SVD analysis run following command from terminal in the project's root directory:

```
$Rscript ./src/analysis.R
```

The resulting plots will be saved "Rplots.pdf" file in the project root. This file will include two plots:

- the plot with relationships between the accuracy of predicting psycho-demographic traits of individuals and the number of the varimax-rotated SVD dimensions used (Figure 1). With this plot, it's easy to visually find an optimal number of  $K$  SVD dimensions to maximize predicting power of regression model per particular psycho-demographic trait of the individual.
- the heat map of correlations between scores of digital footprints of individuals on varimax-rotated SVD dimensions and their psycho-demographic traits (Figure 2). This plot can be used to find most correlated traits visually. Later, it will be shown that predictive models for traits with higher correlation have better prediction accuracy.

### 3.3. Building regression model and prediction results

In our data corpus, we have eight dependent variables with psycho-demographic scores of an individual to be predicted. Among those variables, six have continuous values, and two has categorical values (binominal: 0, 1). To build prediction model for variables with continuous values we will apply linear regression and for variables with categorical values - logistic regression.

#### Linear regression

The linear regression is an approach for modeling the relationship between a scalar dependent variable  $y$  and one or more explanatory variables (or independent variables) denoted  $X$ . The case of one explanatory variable is called simple linear regression. For more than one explanatory variable, the process is called multiple linear regression [David A. Freedman, 2009].

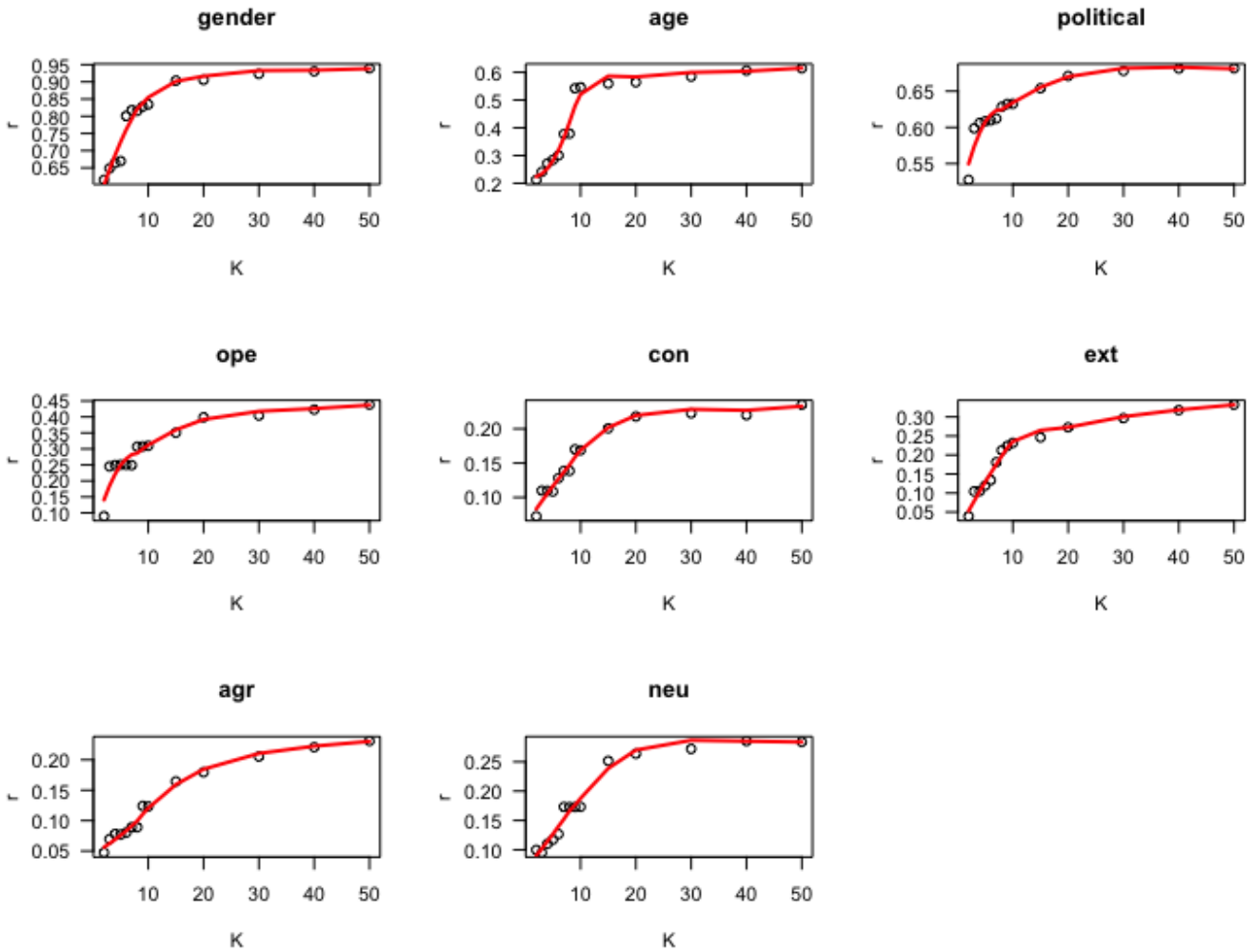
In linear regression, the relationships are modeled using linear predictor function  $y = \Theta^T X$  whose unknown model parameters  $\Theta$  estimated from the input data. Such models are called linear models [Hilary L. Seal, 1967].

#### Logistic regression

The logistic regression is a regression model where the dependent variable is categorical [David A. Freedman, 2009].

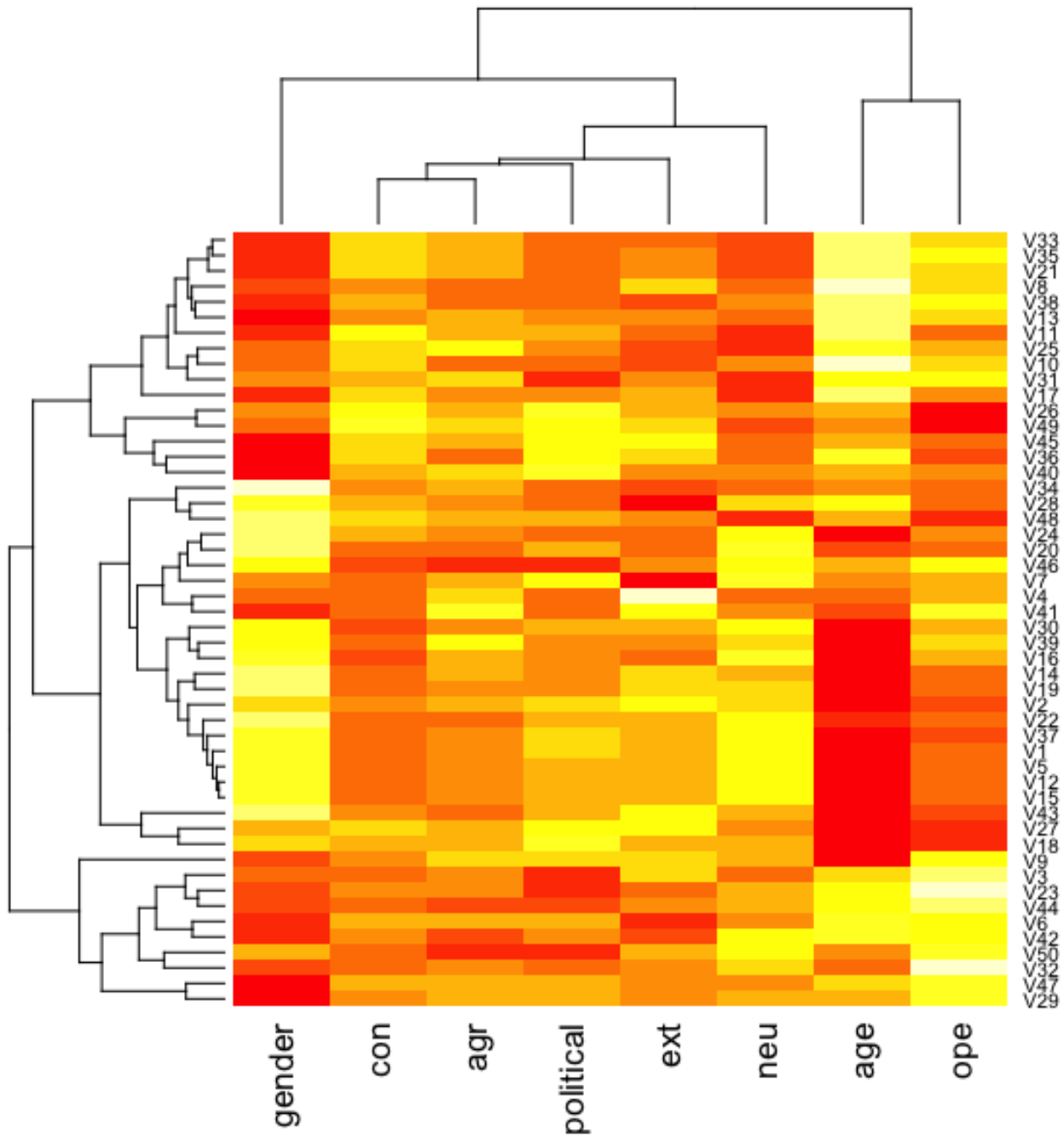
Logistic regression measures the relationship between the categorical dependent variable and one or more independent variables by estimating probabilities using a logistic function  $\sigma(x) = \frac{1}{1+e^{-x}}$ , which is the cumulative logistic distribution [Rodriguez, G., 2007].

In this work we consider only specialized binary logistic regression because dependent variables found in our data corpus are binominal, i.e. have only two possible types, "0" and "1".



**Figure 1:** The relationship between the accuracy of predicting psycho-demographic traits and the number of the varimax-rotated singular value decomposition dimensions used. The results suggest that employing  $K = 50$  SVD dimensions might be a good choice for building models predicting almost all individual's traits of interest, as it offers accuracy that is close to what seems like the higher asymptote for this data. But for Openness, Extroversion, and Agreeableness traits prediction results can be slightly improved with higher values of  $K$  SVD dimensions.





**Figure 2:** The heat map is presenting correlations between  $K = 50$  varimax-rotated singular value decomposition dimensions and scores of psycho-demographic traits of individuals. The heat map suggests that Age, Gender, and the Political view traits have maximum correlation with a maximal number of SVD dimensions. The higher correlation will result in higher prediction power of regression model for particular psycho-demographic traits (which will be shown later).

## Implementing prediction models and accuracy results

The data corpus has eight dependent variables for which to build prediction model. Usually, simple machine learning methods applied with single depend variable to be estimated, but there also exists methods for multivariate regression analysis as well. Taking into account that our dependent variables have different types (continuous and nominal) which require different regression methods to be applied, we have decided to build separate regression models per dependent variable. The metric to evaluate accuracy of prediction model is also dependent on the type of regression method in use, and we have considered the following methods:

- the prediction power of linear regression model will be measured as Pearson product-moment correlation [Gain, 1951]
- the prediction power of logistic regression model will be measured as area under the receiver-operating characteristic curve coefficient (AUC) [Sing, Sander, Beerenwinkel, Lengauer, 2005]

Before executing models make sure that data corpus already pre-processed as described in Subsection: "Construction of sparse users-likes matrix and matrix trimming"

When data corpus is ready, the following command can be executed to start linear/logistic regression models building and its predictive performance evaluation (run command from terminal in the project's root directory):

```
$Rscript ./src/regression_analysis.R
```

The results of predictive performance evaluation will be saved into the file *"out/pred\_accuracy\_regr.txt"*. The results of regression models predictions for data corpus trimmed to contain 150 users-per-like and 50 likes-per-user varimax-rotated against  $K = 50$  SVD dimensions presented in Table 3.

Trait	Variable	Pred. accuracy
Gender	gender	93.65%
Age	age	61.17%
Political view	political	68.36%
Openness	ope	44.02%
Conscientiousness	con	25.72%
Extroversion	ext	30.26%
Agreeableness	agr	23.97%
Neuroticism	neu	29.11%
	Mean	47.03%

**Table 3:** The linear and logistic regression models predictive accuracy results per depended variable.

From the Table 3 we can see that prediction power of simple linear and logistic regression models differs for each dependent variable and for most outputs the obtained prediction accuracies is not enough to be used for real-life predictions. The most accurate predictions made for *Gender*, *Age*, and *Political view* with *Openness* following next. That correlates well with our previous analysis of SVD correlations heat map (Figure 2). In general only prediction model for *Gender* is accurate enough to be useful in real-life applications.

In following sections, we will consider applying of advanced deep machine learning techniques to improve prediction accuracy.

## 4. FULLY CONNECTED FEED FORWARD ARTIFICIAL NEURAL NETWORKS

In this work, we will consider multilayer fully connected feed-forward neural networks (NN) for building simple or shallow (single hidden layer) and deep machine learning NN models. In fully connected NN all neurons of current layer connected with each neuron of the previous layer. The feed-forward NN is not allowed to have cycles from latter layers back to the earlier.

The models based on NN architecture can have one or multiple hidden layers. When only one hidden layer present, its nodes (neurons) take inputs from input nodes (columns of input data matrix) and feeds into the output nodes, where linear or categorical analysis performed. If the network includes two or more hidden layers, then the first hidden layer will take inputs from each of the input nodes and the subsequent hidden layer will take inputs from each of previous hidden layer nodes outputs [Christopher M. Bishop, 1995].

Artificial neural networks (ANN) are prone to overfitting because of the added layers of abstraction, which allow them to model rare dependencies in the training data. Various regularization methods can be applied during training to help reduce overfitting. One of the promising methods to reduce overfitting is *dropout* regularization, where some number of units (neurons) randomly omitted from the hidden layers during training. This helps to break the rare dependencies that can occur in the training data [Hinton, G. et al., 2012].

### 4.1. The shallow Feed Forward ANN evaluation

A shallow neural network (SNN) is an artificial neural network with one hidden layer of units (neurons) between input and output layers. To mimic biological neuron, hidden units in the network apply specific non-linear activation functions. One of popular activation functions is ReLU non-linearity that we considered as activation function for the hidden layers units in studied network architectures [Nair, Hinton, 2010].

The ReLU non-linearity was selected as it improves information disentangling and linear separability producing efficient variable size representation of model's data [Glorot, Bordes, Bengio, 2011].

*When applying rectified non-linearity (ReLU), we can consider the predictive model as an exponential number of linear models that share parameters. Because of this linearity, gradients flow well on the active paths of neurons (there is no gradient vanishing effect due to activation non-linearities as in case of sigmoid or tanh activation units), and as a result, the mathematical investigation is easier. Computations are also cheaper: there is no need for computing the exponential function in activations, and sparsity can be exploited [Glorot, Bordes, Bengio, 2011].*

To reduce overfitting was selected dropout regularization with drop-probability 0.5, which means that each hidden unit if randomly omitted from the network with the specified probability.

*The other way to view the dropout procedure is as a very efficient way of performing model averaging with neural networks. A good way to reduce the error on the test set is to average the predictions produced by a vast number of different networks. The standard way to do this is to train many separate networks and then to apply each of these networks to the test data, but this is computationally expensive during both training and testing. Random dropout makes it possible to train a huge number of different networks in a reasonable time. There is almost certainly a different network for each presentation of each training case, but all of these networks share the same weights for the hidden units that are present [Hinton, G. et al., 2012].*

The NN architecture was build using Google Brain's TensorFlow library - an open source software library for numerical computation using data flow graphs. [Google Brain Team, 2015] Nodes in the graph represent mathematical operations, while the graph edges represent the multidimensional data arrays (tensors) communicated between them. The resulting two layer (one hidden layer) ANN's architecture graph depicted in Figure 5

It was found that optimal number of SVD dimensions with two-layer ANN is  $K = 128$ , and number of units in the hidden layer is 512, with learning rate value  $\gamma = 0.0001$ , see Table 4. As *loss function* to be optimized was selected *Mean Squared Error* (MSE) with *Adam* optimizer (Adaptive Moment Estimation) to estimate it's minimum. The Adam optimizer was selected for *it's proven advantages some of them are that the magnitudes of parameter updates are invariant to rescaling of the gradient, its step sizes are approximately bounded by the step size hyper-parameter, it does not require a stationary objective, it works with sparse gradients, and it naturally performs a form of step size annealing* [Kingma, Ba, 2014]. The batch size was selected to be 100. We also tested training with batch size 10 but found no statistically relevant prediction accuracy difference between runs with either batch size.

Trait	Variable	Prediction accuracy, $\gamma = 0.0001$			
		$K = 50$	$K = 128$	$K = 256$	$K = 512$
Gender	gender	93.76%	93.61%	93.00%	93.82%
Age	age	85.00%	85.07%	85.03%	83.59%
Political view	political	66.65%	66.86%	67.28%	65.32%
Openness	ope	47.22%	51.24%	47.26%	44.81%
Conscientiousness	con	28.56%	28.45%	29.65%	28.26%
Extroversion	ext	32.53%	32.87%	30.44%	30.32%
Agreeableness	agr	25.21%	27.66%	24.58%	24.80%
Neuroticism	neu	33.53%	36.24%	33.09%	31.96%
	Mean	51.58%	52.75%	51.29%	50.36%

**Table 4:** The predictive accuracy results of SNN per  $K$  SVD dimensions with learning rate  $\gamma = 0.0001$  and 512 units in the hidden layer.

The learning rate was selected by watching ratio of survived hidden units with *non zero ReLU activation* and monitoring loss function over iterations plot (Figure 3). With presented hyper-parameters it was achieved maximum ratio 0.57 of zero ReLU activations for highest learning rate, which fairly good taking into account tendency of ReLU to saturate at zero during gradient back propagation stage when strong gradients applied, due to high learning rates [Nair, Hinton, 2010]. The maximal number of iterations (50 000) and correspondingly number of training epochs was selected based on loss function plot (Figure 3). With series of experiments it was selected as optimal the learning rate value  $\gamma = 0.0001$ , which gives smooth loss function, minimal number of "dead" neurons after ReLU activation (ReLU zero activations ratio is about 0.5), and best prediction scores among runs (see Table 5).

Trait	Variable	Prediction accuracy, $K = 128$ SVD		
		$\gamma = 0.001$	$\gamma = 0.0001$	$\gamma = 0.00001$
Gender	gender	93.88%	93.61%	91.97%
Age	age	83.68%	85.07%	73.81%
Political view	political	66.67%	66.86%	66.95%
Openness	ope	49.43%	51.24%	45.92%
Conscientiousness	con	27.18%	28.45%	27.79%
Extroversion	ext	29.93%	32.87%	31.93%
Agreeableness	agr	25.38%	27.66%	24.51%
Neuroticism	neu	31.15%	36.24%	32.24%
	Mean	50.91%	52.75%	49.39%

**Table 5:** The predictive accuracy results of SNN per learning rate with  $K = 128$  SVD dimensions and 512 units in the hidden layer.

The accompanying launch script provided to conduct experiments under Unix:

```
$. /eval_mlp_1.sh ul_svd_matrix_file
```

where: `ul_svd_matrix_file` the path to the users-likes matrix with features columns dimensionality reduced with SVD method against selected number of  $K = 128$  SVD dimensions

The source code of shallow ANN implementation used for experiment can be found in `src/mlp.R` of accompanying GitHub repository.

## 4.2. Feed Forward Deep Learning Network

A deep neural network (DNN) is an artificial neural network with multiple hidden layers of units between the input and output layers. Similar to shallow, deep neural network can model complex non-linear relationships. The added extra layers enable composition of features from lower layers, giving the potential of modeling complex data with fewer units than a similarly performing shallow network [Bengio, Yoshua, 2009].

*Deep learning discovers intricate structure in large data sets by using the backpropagation algorithm to indicate how a machine should change its internal parameters that are used to compute the representation in each layer from the representation in the previous layer [LeCun, Bengio, Hinton, 2015].*

As with shallow ANNs, many issues can arise with DNNs training, with two most common problems - are overfitting and computation time [Tetko, Livingstone, Luik, 1995].

### The three-layer Deep Learning Network

Our experiments with deep learning networks we started with simple DNN architecture comprising of two hidden layers with ReLU activation and dropout after each hidden layer with keep probability of 0.5. The experimental network graph depicted in Figure 7.

		Prediction accuracy, $\gamma = 0.0001$				
		$K = 50$	$K = 128$	$K = 256$	$K = 512$	$K = 1024$
Trait	Variable	512,256	512,256	512,256	1024,512	2048,1024
Gender	gender	92.60%	92.14%	92.53%	93.61%	95.68%
Age	age	85.03%	82.97%	80.67%	81.45%	82.53%
Political view	political	66.66%	67.34%	67.06%	67.26%	65.06%
Openness	ope	44.76%	47.56%	47.68%	46.39%	40.61%
Conscientiousness	con	24.33%	25.79%	25.68%	27.74%	24.67%
Extroversion	ext	30.86%	32.35%	34.35%	28.16%	26.53%
Agreeableness	agr	24.83%	25.66%	26.48%	21.65%	29.90%
Neuroticism	neu	32.17%	33.01%	35.94%	28.50%	30.83%
Mean		50.15%	50.85%	51.30%	49.34%	49.48%

**Table 6:** The predictive accuracy results of three layer DNN per  $K$  SVD dimensions with learning rate  $\gamma = 0.0001$ , with sizes of hidden layers presented in third table header row as  $[hidden_1, hidden_2]$ .

We have started with learning rate  $\gamma = 0.0001$  which had shown best results for shallow ANN and attempted series of experiments to estimate optimal value of  $K$  SVD dimensions. The optimal prediction accuracy of DNN

model achieved with  $K = 256$  SVD dimensions and two hidden layers with [512, 256] units correspondingly. Similar prediction accuracy also achievable with  $K = 1024$  SVD dimensions and [2048, 1024] units per layer with learning rate  $\gamma = 10^{-5}$ . But we have not considered hyper-parameters due to its extra overhead for computation while giving statistically same results as with former. The results of experiments presented in Table 6.

After finding optimal values for  $K$  SVD dimensions and number of units per hidden layer, we have conducted series of experiments to determine optimal learning rate value. See Table 7

Trait	Variable	Prediction accuracy, $K = 256$ SVD		
		$\gamma = 0.001$	$\gamma = 0.0001$	$\gamma = 0.00001$
Gender	gender	90.89%	92.53%	82.75%
Age	age	79.60%	80.67%	79.44%
Political view	political	67.33%	67.06%	59.69%
Openness	ope	44.73%	47.68%	39.48%
Conscientiousness	con	21.41%	25.68%	22.86%
Extroversion	ext	24.62%	34.35%	24.07%
Agreeableness	agr	17.27%	26.48%	16.34%
Neuroticism	neu	27.72%	35.94%	28.53%
	Mean	46.70%	51.30%	44.14%

**Table 7:** The predictive accuracy results of three layer DNN per learning rate with  $K = 256$  SVD dimensions, and with sizes of hidden layers 512 and 256 correspondingly.

In our experiments, we have applied exponential learning rate decay with the number of steps before decay 10000 and decay rate of 0.96. Such scheme results in the positive effect on network convergence speed due to learning rate annealing effect, which gives a system the ability to escape from poor local minima to which it might have been initialized [Kirkpatrick et al., 1983]. We selected batch size 100 as optimal for this experiment.

The accompanying launch script provided to conduct experiments under Unix:

```
$/eval_dnn.sh ul_svd_matrix_file
```

where: `ul_svd_matrix_file` the path to the users-likes matrix with features columns dimensionality reduced with SVD method against selected number of  $K$  SVD dimensions

The source code of DNN with two hidden layers implementation used for experiment can be found in `src/dnn.R` of accompanying GitHub repository.

### The four-layer Deep Learning Network

This architecture includes three hidden layers with ReLU activation and one output linear layer. All network layers are fully connected and network architecture is feed-forward as in all previous NN experiments. The experimental network graph depicted in Figure 8.

We have tested two dropout regularization schemes: (a) dropout applied after each hidden layer with keep-probability 0.5; (b) dropout applied after each second hidden layer with keep probability calculated by formula:  $p_d = \frac{i}{2n}$ , (where:  $n$  - number of dropouts,  $i$  - current dropout index). It was found that former scheme gives better results than last one, thus for final evaluation run, we applied dropout regularization after each hidden layer.

		Prediction accuracy, $\gamma = 0.0001$			
		$K = 128$	$K = 256$	$K = 512$	$K = 1024$
Trait	Variable	256,128,128	512,256,256	1024,512,512	2048,1024,1024
Gender	gender	55.07%	70.63%	92.13%	91.03%
Age	age	83.82%	82.78%	83.80%	84.96%
Political view	political	57.42%	61.23%	64.52%	66.52%
Openness	ope	13.52%	27.50%	44.88%	44.86%
Conscientiousness	con	14.41%	14.92%	20.76%	28.72%
Extroversion	ext	4.06%	7.30%	22.77%	26.85%
Agreeableness	agr	10.12%	10.90%	17.69%	20.02%
Neuroticism	neu	8.81%	11.98%	27.48%	28.97%
Mean		30.91%	35.90%	46.75%	48.99%

**Table 8:** The predictive accuracy results of three layer DNN per  $K$  SVD dimensions with the learning rate  $\gamma = 0.0001$ . The number of units in hidden layers differ per configuration and presented as  $[hidden_1, hidden_2]$  in third table header row

Based on our previous experiments with more shallow networks we decided to start with following hyper-parameters for four-layer network architecture: learning rate  $\gamma = 0.0001$ , learning rate decay step 10 000 with decay rate 0.96,  $K = 128$  SVD dimensions, and layers configuration:  $[256, 128, 128]$ . We have conducted series of experiments to find the optimal number of  $K$  SDV dimensions and hidden layers configuration. The heuristic behind selecting the number of units per hidden layer was rather naive and assumes that with dropout probability 0.5 half of the units will be saturated to zero at ReLU activation. Thus we decided to have the number of units in the first hidden layer to be twice as much as the number of features in input data ( $K$ ). The results of experiment present in Table 8

Despite the fact that best accuracy was achieved with  $K = 1024$  and the number of units in hidden layers  $[2048, 1024, 1024]$  respectively, it was detected severe model overfitting with train data set for specified parameters. So, we have decided to stop increasing  $K$  and sizes of hidden units as it will give no significant further gain in prediction accuracy against validation data set (see Figure 6).

The accompanying launch script provided to conduct experiments under Unix:

```
$/ eval_3dnn.sh ul_svd_matrix_file
```

where: `ul_svd_matrix_file` the path to the users-likes matrix with features columns dimensionality reduced with SVD method against selected number of  $K$  SVD dimensions

The source code of DNN with two hidden layers implementation used for experiment can be found in `src/3dnn.R` of accompanying GitHub repository.

## 5. FUTURE WORK

From our experiments, we found that prediction accuracy per each dependent variable differs among machine learning methods applied and best results achieved by using advanced machine learning methods based on neural networks algorithms. At the same time, the prediction accuracy per dependent variable also differs between studied models. It was found that specific combinations of NN architecture and hyper-parameters are best suited for specific dependent variables, but lacking predictive power for the others. In future experiments, it is interesting to investigate

this dependency and build separate NN models per each dependent variable as it was done in case of simple machine learning methods (see Section: ‘Regression analysis’)

Also, it seems promising to apply methodology described in [Ba, Caruana, 2014] which provide evidence that shallow networks are capable of learning the same functions as deep learning networks, and often with the same number of parameters as the deep learning networks. In [Ba, Caruana, 2014] it was shown that with wide shallow networks it’s possible to reach the state-of-the-art performance of deep models and reduce training time by the factor of 10 using parallel computational resources (GPU).

## 6. CONCLUSION

In our experiments we have found that weak correlation exists between most of O.C.E.A.N. psychometric traits of individuals and collected Facebook likes associated with them. Either simple or advanced machine learning algorithms that we have tested provided *poor prediction accuracy* for almost all O.C.E.A.N. personality traits. It seems not feasible yet to use machine learning models to precisely estimate *psychometric profile* of an individual.

At the same time we have found strong correlation with *demographic traits* of individuals such as *Age*, *Gender* and the *Political Views*, which makes it feasible to apply advanced machine learning methods to create demographic profile of an individual.

Trait	Variable	DNN			
		Regression K = 50	SNN K = 128	512,256 K = 256	2048,1024,1024 K = 1024
Gender	gender	93.65%	93.61%	92.53%	91.03%
Age	age	61.17%	85.07%	80.67%	84.96%
Political view	political	68.36%	66.86%	67.06%	66.52%
Openness	ope	44.02%	51.24%	47.68%	44.86%
Conscientiousness	con	25.72%	28.45%	25.68%	28.72%
Extroversion	ext	30.26%	32.87%	34.35%	26.85%
Agreeableness	agr	23.97%	27.66%	26.48%	20.02%
Neuroticism	neu	29.11%	36.24%	35.94%	28.97%
	Mean	47.03%	52.75%	51.30%	48.99%

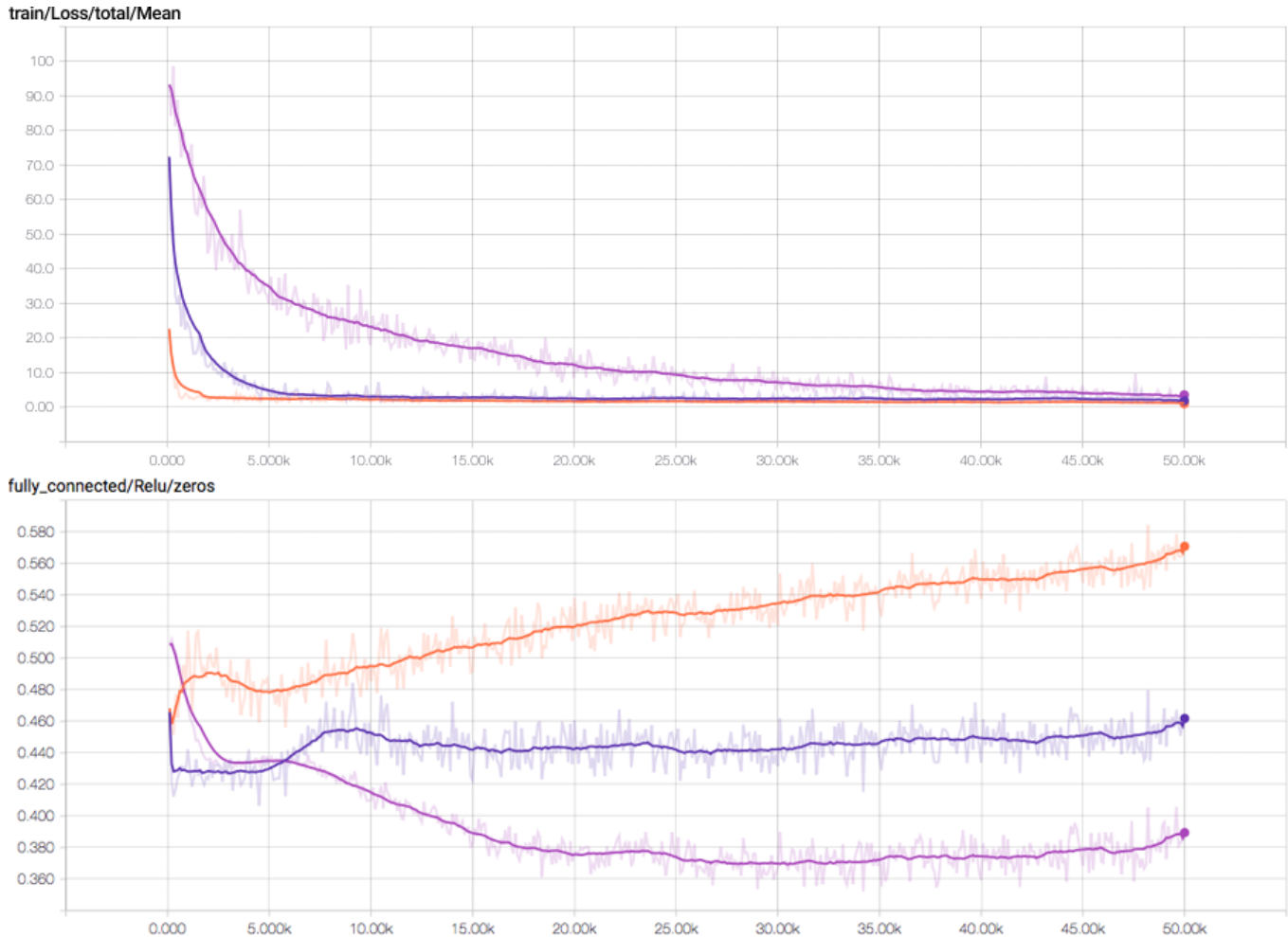
**Table 9:** The comparison of predictive accuracy for best prediction models found during experiments. The average prediction accuracy demonstrated by shallow neural network (SNN) with tree-layer deep neural network (DNN [512,256]) following next. The further increase of K SVD dimensions and adding of additional hidden layers results in train overfitting and degradation of prediction accuracy over validation data set.

Among all tested machine learning methods the best overall prediction accuracy was achieved with shallow neural network architecture. We hypothesize this may be the result of its ability to learn best parameters space function within an optimal number of *SVD dimensions* applied to the raw input data set (users-likes sparse matrix). Adding additional hidden layers either leads to model *overfitting* when the number of SVD dimensions is too high, or *underfitting* otherwise compared to the shallow network. Also, it’s interesting to notice that performance of shallow networks and deep learning networks with two hidden layers are comparable, while with introducing of third and more hidden layers it drops significantly. Thus we can conclude that no further improvements can be gained with extra hidden layers inserted. See Table 9.

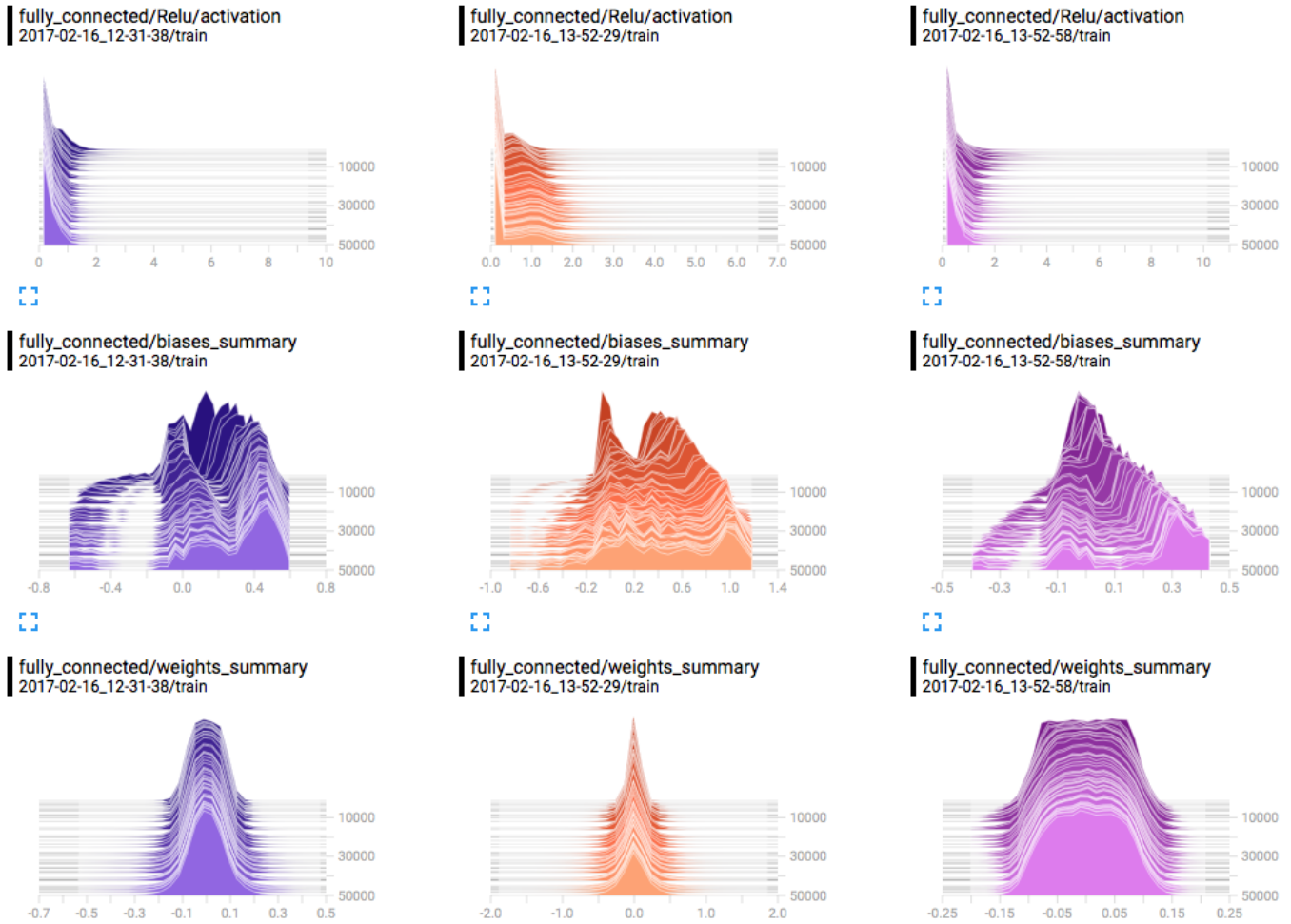


## A. THE SNN EVALUATION PLOTS

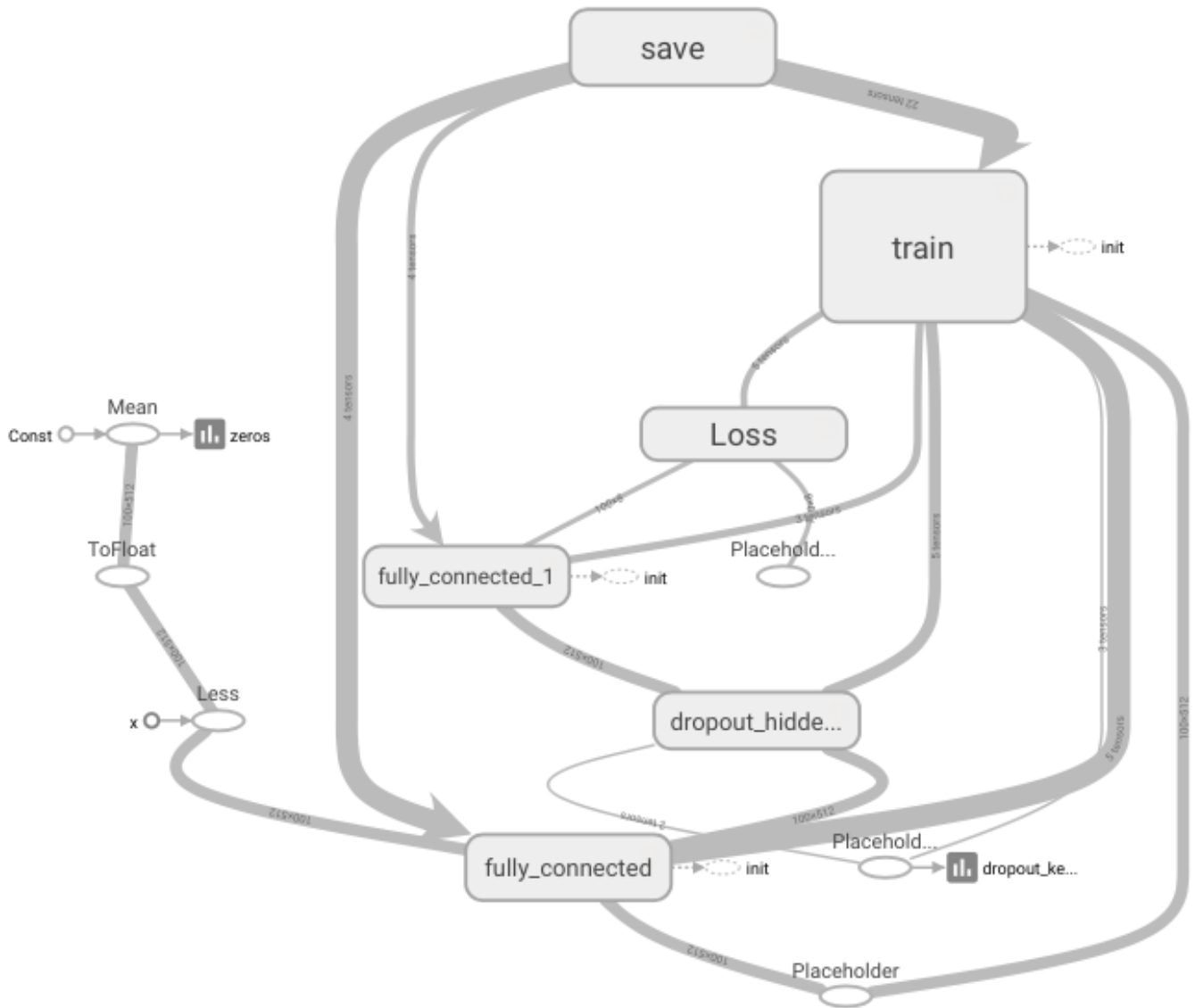
The following pages provide plots and diagrams related to evaluation of two layer (shallow) feed forward artificial neural network with one fully connected hidden layer and linear output layer.



**Figure 3:** The training process evaluation based on loss values and ReLU zero activations per number of iterations. With higher learning rate ( $\gamma = 0.001$  - orange) we have fast convergence but ratio of ReLU-zero activations is higher than 0.5 and quickly rising with relatively low evaluated prediction accuracy, which implies that optimum was missed. With medium learning rate ( $\gamma = 0.0001$  - violet) we have smooth loss function plot with ratio of ReLU-zero activations bellow 0.5, giving best prediction scores among all three runs. With lowest learning rate ( $\gamma = 0.00001$  - purple) we can see that learning struggled to find global minimum, reduced speed of convergence, and despite the lowest ReLU zero activations rate - worst prediction accuracy among all runs due to high loss values.



**Figure 4:** The histograms of various tensors collected during three runs within hidden layer (Left:  $\gamma = 0.0001$ , middle:  $\gamma = 0.001$ , right:  $\gamma = 0.00001$ ). By examining weights histograms it may be noticed that middle has widest base with sharp peak which means that layer converged, but search space was widest among all runs. The left one has narrower base and sharp peak, which means that layer converged withing narrower search space and as result has better prediction power. The right one has narrow base but wide plateau at the top, which means that search space is narrow but algorithm still failed to converge. The left and middle histograms has sharp peaks compared to right one, which may be a signal that their learning rate values has more relevance for algorithm convergence and as result we have better predictions for those learning rates.

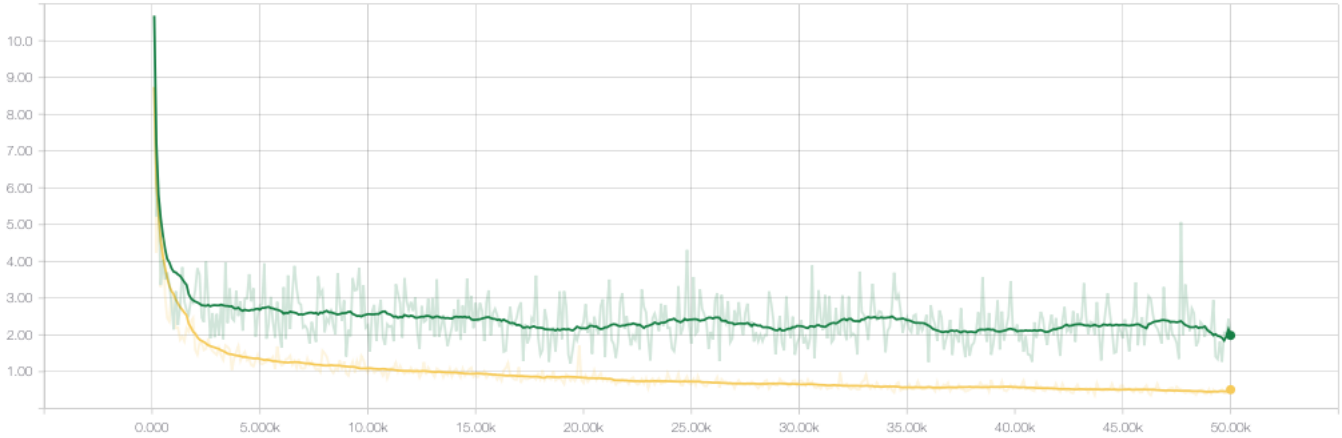


**Figure 5:** The tensor network graph for multi layer perceptron with one hidden layer (fully\_connected), and one linear output layer (fully\_connected1). The input layer presented as input tensor placeholder. The hidden layer has ReLU activation nonlinearity. The loss function is MSE (mean squared error). The train optimizer is Adam (for Adaptive Moment Estimation).

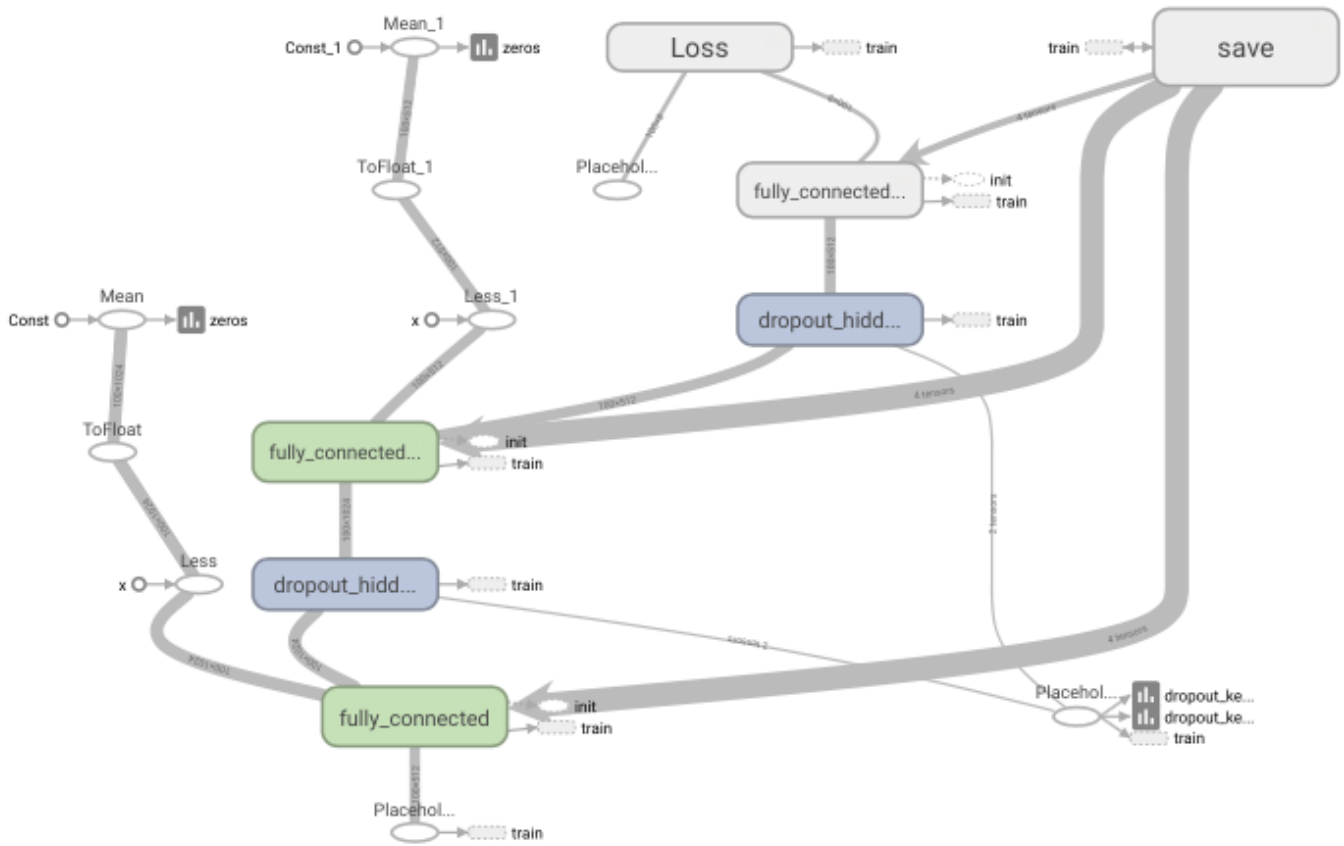
## B. DEEP NN EVALUATION PLOTS

The following pages provide plots and diagrams related to evaluation of studied deep neural networks.

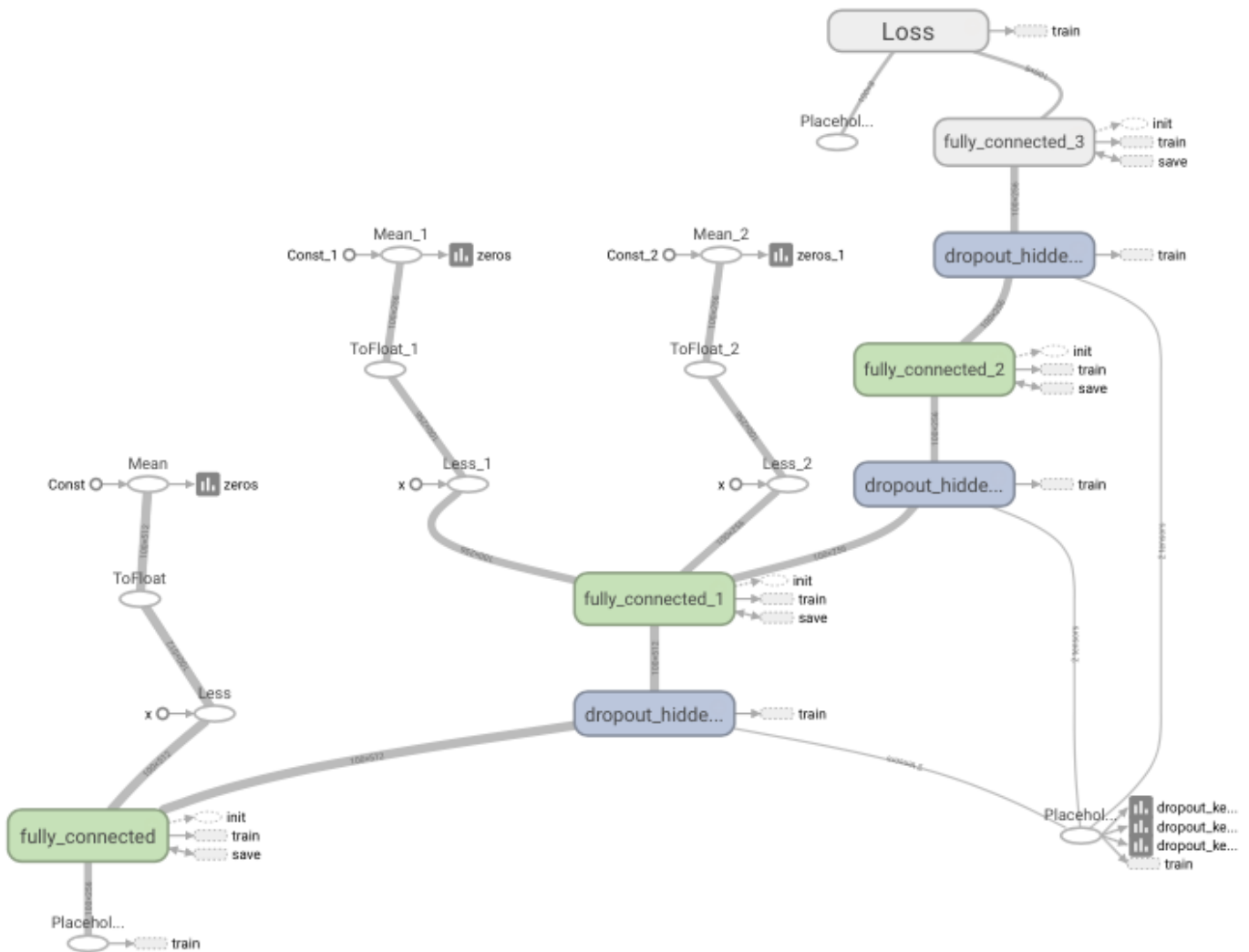
train/Loss/total/Mean



**Figure 6:** The loss function plot against *train* and *validation* data sets, for  $K = 1024$  input features and three hidden layers with  $[2048,1024,1024]$  units per layer correspondingly. It can be seen that model overfitted against training data and as result no further improvements over validation data can be gained with more training steps.



**Figure 7:** The tensor network graph for DNN with two hidden layers. The input layer presented as input tensor placeholder. The hidden layers has ReLU activation nonlinearity. The loss function is MSE (mean squared error). The train optimizer is Adam (for Adaptive Moment Estimation).



**Figure 8:** The tensor network graph for DNN with three hidden layers. The input layer presented as input tensor placeholder. The hidden layers has ReLU activation nonlinearity. The loss function is MSE (mean squared error). The train optimizer is Adam (for Adaptive Moment Estimation).

## REFERENCES

- [Kosinski et. al, 2016] Michal Kosinski, Yilun Wang, Himabindu Lakkaraju, and Jure Leskovec, (2016). Mining Big Data to Extract Patterns and Predict Real-Life Outcomes. *Psychological Methods* 2016, Vol. 21, No. 4, 493-506. DOI: 10.1037/met0000105
- [Lambiotte, R., and Kosinski, M., 2014] Lambiotte, R., and Kosinski, M., (2014). Tracking the digital footprints of personality. *Proceedings of the Institute of Electrical and Electronics Engineers*, 102, 1934-1939. DOI: 10.1109/JPROC.2014.2359054
- [Goldberg et. al, 2006] Goldberg, L. R., Johnson, J. A., Eber, H. W., Hogan, R., Ashton, M. C., Cloninger, C. R., and Gough, H. G. (2006). The International Personality Item Pool and the future of public-domain personality measures. *Journal of Research in Personality*, 40, 84-96. DOI: 10.1016/j.jrp.2005.08.007
- [Golub, G. H., and Reinsch, C. 1970] Golub, G. H., and Reinsch, C. (1970). Singular value decomposition and least squares solutions. *Numerische Mathematik*, 14, 403-420. DOI: 10.1007/BF02163027
- [Abdi, H., 2003] Abdi, H. (2003). Factor rotations in factor analyses. In M. Lewis-Beck, A. E. Bryman, & T. F. Liao (Eds.), *The SAGE encyclopedia of social science research methods* (pp. 792-795). Thousand Oaks, CA: SAGE.
- [Goodfellow et al., 2016] Ian Goodfellow and Yoshua Bengio and Aaron Courville, (2016). *Deep learning*. Manuscript in preparation. Retrieved from <http://www.deeplearningbook.org/>
- [Daphne Koller, 2012] Daphne Koller, (2010-2012) *Probabilistic Graphical Models*. Stanford University. Retrieved from <http://openclassroom.stanford.edu/MainFolder/CoursePage.php?course=ProbabilisticGraphicalModels>
- [Cortes & Vapnik, 1995] Cortes, C. & Vapnik, V. (1995). Support-vector networks. *Machine Learning*. 20 (3):273-297. DOI: 10.1007/BF00994018
- [Yan, Su, 2009] Xin Yan, Xiao Gang Su, (2009), *Linear Regression Analysis: Theory and Computing*, World Scientific, pp. 1-2, ISBN 9789812834119
- [David A. Freedman, 2009] David A. Freedman (2009). *Statistical Models: Theory and Practice*. Cambridge University Press, p. 26.
- [Hilary L. Seal, 1967] Hilary L. Seal (1967). The historical development of the Gauss linear model. *Biometrika*. 54 (1/2): 1-24. DOI: 10.1093/biomet/54.1-2.1
- [Rodriguez, G., 2007] Rodriguez, G. (2007). *Lecture Notes on Generalized Linear Models*. pp. Chapter 3, page 45. Retrieved from <http://data.princeton.edu/wws509/notes/>
- [Sing, Sander, Beerenwinkel, Lengauer, 2005] Sing, T., Sander, O., Beerenwinkel, N., & Lengauer, T. (2005). ROC: Visualizing classifier performance in R. *Bioinformatics*, 21, 3940-3941. DOI: 10.1093/bioinformatics/bti623
- [Gain, 1951] Gain, A. K. (1951). The frequency distribution of the product moment correlation coefficient in random samples of any size draw from non-normal universes. *Biometrika*. 38: 219-247. DOI: 10.1093/biomet/38.1-2.219
- [Kohavi, Ron, 1995] Kohavi, Ron (1995). A study of cross-validation and bootstrap for accuracy estimation and model selection. *Proceedings of the Fourteenth International Joint Conference on Artificial Intelligence*. San Mateo, CA: Morgan Kaufmann. 2 (12): 1137-1143. CiteSeerX 10.1.1.48.529
- [Zhang, Marron, Shen, & Zhu, 2007] Zhang, L., Marron, J., Shen, H., & Zhu, Z. (2007). Singular value decomposition and its visualization. *Journal of Computational and Graphical Statistics*, 16, 833-854.

- [van Buuren, Groothuis-Oudshoorn, 2011] Stef van Buuren and Karin Groothuis-Oudshoorn (2011). mice: Multivariate Imputation by Chained Equations in R. *Journal of Statistical Software* 45 (3) American Statistical Association. Retrieved from <http://doc.utwente.nl/78938/>
- [Rubin DB, 1987] Rubin DB (1987). *Multiple Imputation for Nonresponse in Surveys*. John Wiley & Sons, New York.
- [Christopher M. Bishop, 1995] Christopher M. Bishop (1995). *Neural Networks for Pattern Recognition*, Oxford University Press, Inc. New York, NY, USA ©1995 ISBN:0198538642
- [Bengio, Yoshua, 2009] Bengio, Yoshua (2009). Learning Deep Architectures for AI. *Foundations and Trends in Machine Learning*. 2 (1): 1-127. DOI: 10.1561/22000000006
- [LeCun, Bengio, Hinton, 2015] LeCun, Yann; Bengio, Yoshua; Hinton, Geoffrey (2015). Deep learning. *Nature*. 521: 436-444. DOI:10.1038/nature14539
- [Tetko, Livingstone, Luik, 1995] Tetko, I. V.; Livingstone, D. J.; Luik, A. I. (1995). Neural network studies. 1. Comparison of Overfitting and Overtraining. *J. Chem. Inf. Comput. Sci.* 35 (5): 826-833. DOI: 10.1021/ci00027a006
- [Hinton, G. et al., 2012] Hinton, Geoffrey E.; Srivastava, Nitish; Krizhevsky, Alex; Sutskever, Ilya; Salakhutdinov, Ruslan R. (2012). *Improving neural networks by preventing co-adaptation of feature detectors*. arXiv preprint arXiv:1207.0580v1
- [Nair, Hinton, 2010] Vinod Nair and Geoffrey Hinton (2010). Rectified linear units improve restricted Boltzmann machines. *ICML*. Retrieved from [http://machinelearning.wustl.edu/mlpapers/paper\\_files/icml2010\\_NairH10.pdf](http://machinelearning.wustl.edu/mlpapers/paper_files/icml2010_NairH10.pdf)
- [Glorot, Bordes, Bengio, 2011] Xavier Glorot, Antoine Bordes, Yoshua Bengio (2011). Deep Sparse Rectifier Neural Networks. *JMLR W&CP* 15:315-323 Retrieved from <http://jmlr.org/proceedings/papers/v15/glorot11a.html>
- [Kingma, Ba, 2014] Diederik P. Kingma; Lei Jimmy Ba (2014). *Adam: A method for stochastic optimization*. arXiv preprint arXiv:1412.6980
- [Ba, Caruana, 2014] Lei Jimmy Ba, Rich Caruana (2014). *Do Deep Nets Really Need to be Deep?* arXiv preprint arXiv:1312.6184
- [Kirkpatrick et al., 1983] S. Kirkpatrick, C. D. Gelatt Jr., M. P. Vecchi (1983). Optimization by Simulated Annealing. *Science*, 13 May 1983: Vol. 220, Issue 4598, pp. 671-680 DOI: 10.1126/science.220.4598.671
- [R Core Team, 2015] R Core Team, (2015). R: A language and environment for statistical computing. *Vienna, Austria: R Foundation for Statistical Computing*. Retrieved from <http://www.R-project.org/>
- [Google Brain Team, 2015] Google Brain Team, (2015). TensorFlow is an open source software library for numerical computation using data flow graphs. Retrieved from <https://www.tensorflow.org>