

# Prediction Customer Behaviour: SVM and Neural Network

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# Viewing the dataset

- Unbalanced Dataset:  
1-2% of customers

# Viewing the dataset

- Unbalanced Dataset:  
1-2% of customers
- A focus on the dataset:  
Demographics  
Account Balance  
Change in Account Balance  
TMD Expiration Date  
Previous Wealth Purchases

# First Step:

## Identifying Pairwise Connections

### **Intuition:**

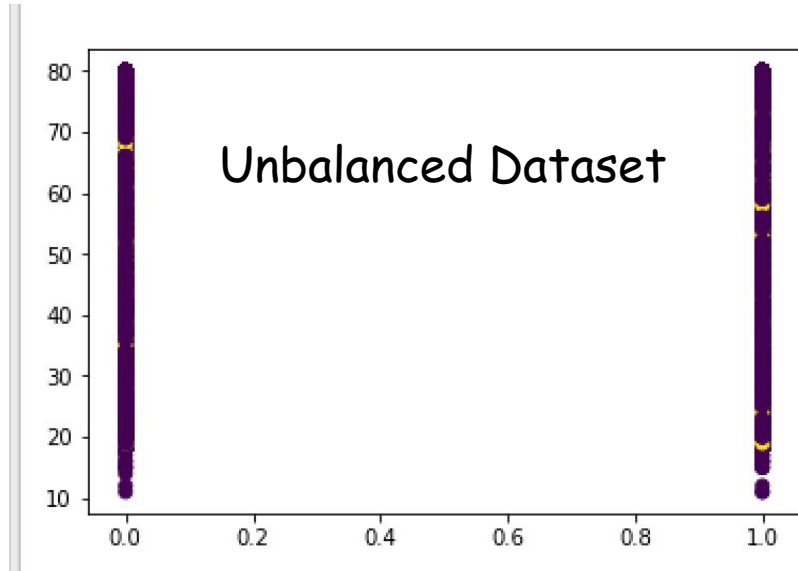
Some of the features, might be the key factor of determining wealth purchases.

### **Expectation:**

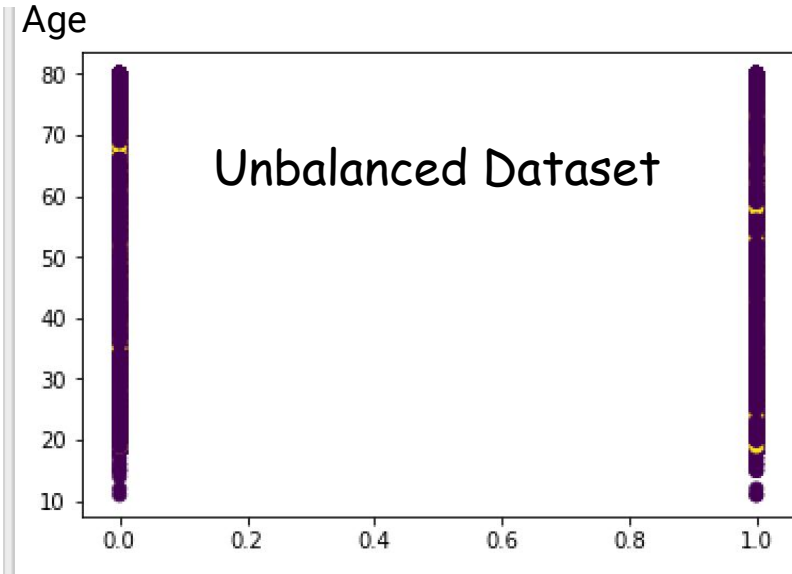
We expect that some of the factors may be positively deterministic and some are vice versa.

For example, it may be of high probability that a person travelling abroad will buy insurance.

# Age, gender and Purchases?



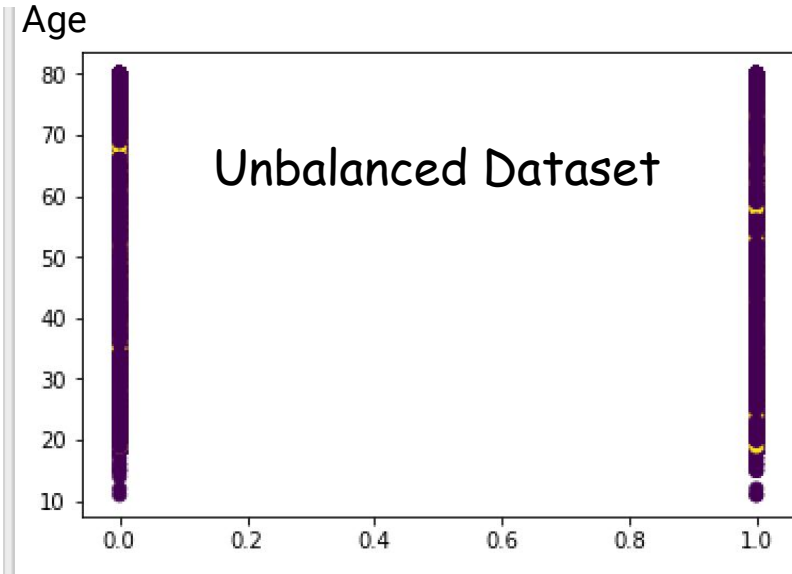
# Age and Purchases?



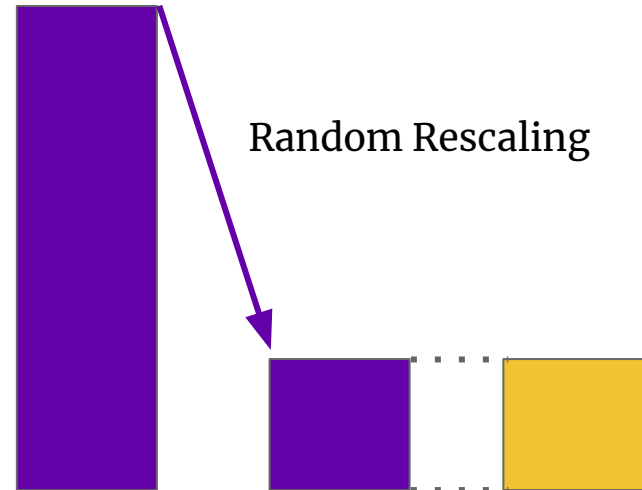
- We use random rescaling to remove the unbalance



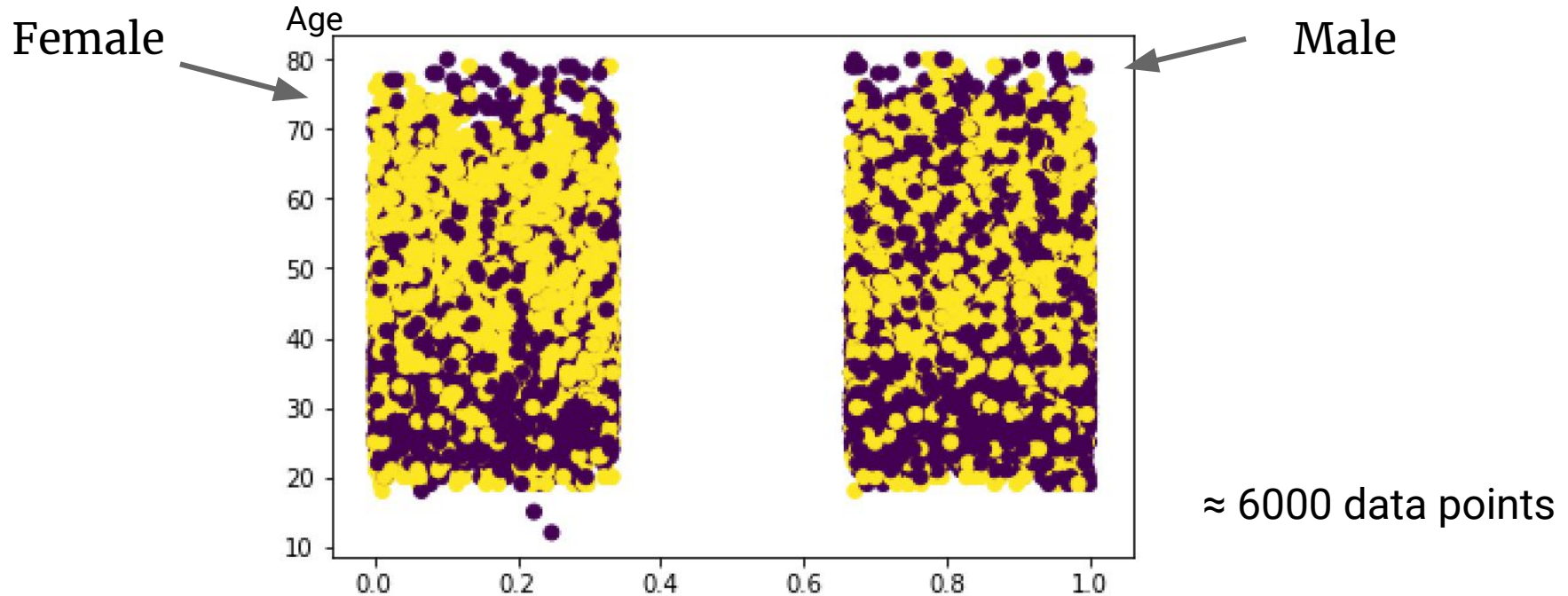
# Age and Purchases?



We use random rescaling to remove the unbalance

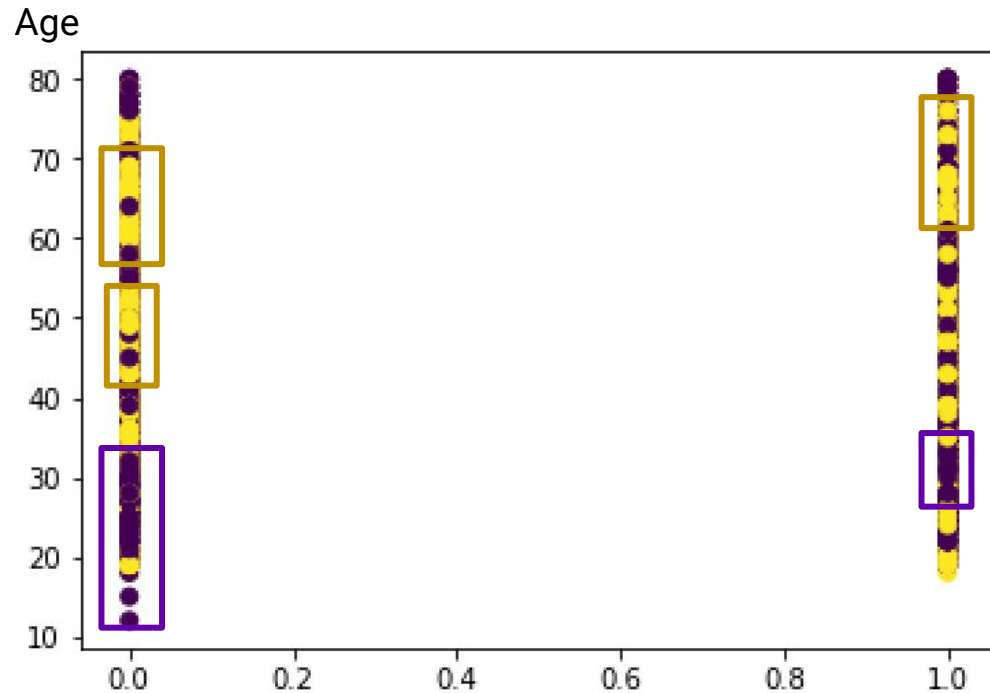


# Age and Purchases?





# Intuition: Key areas



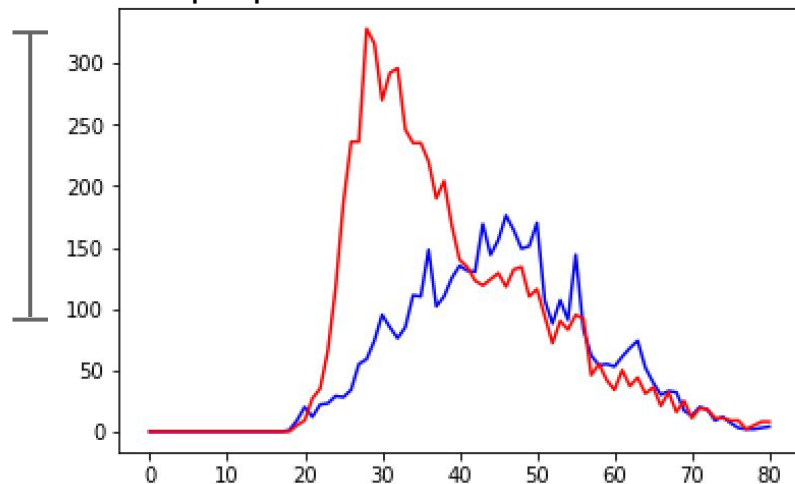
# Finally,

— People who purchased

— People who did not purchase

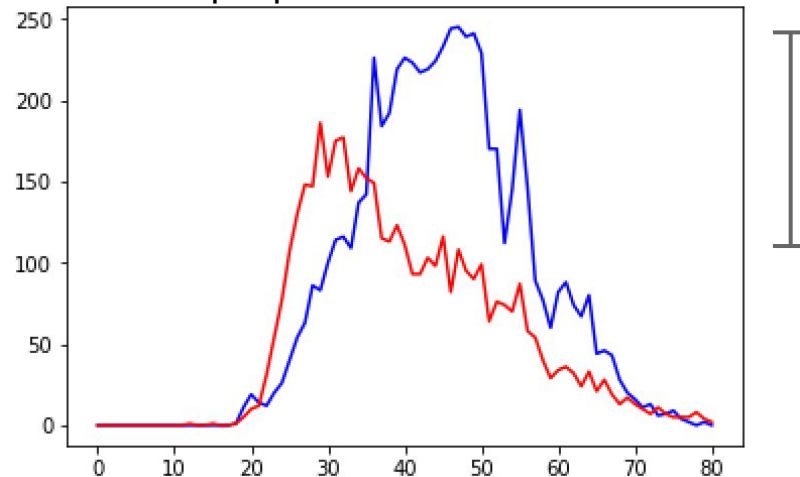
Male:

Number of people



Female:

Number of people



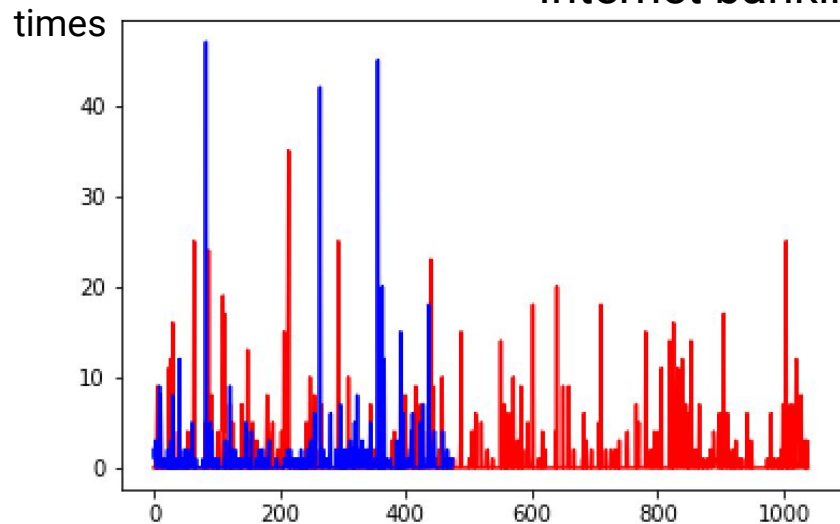
Similarly, we can identify these relations  
between other pairwise features

# Transaction?

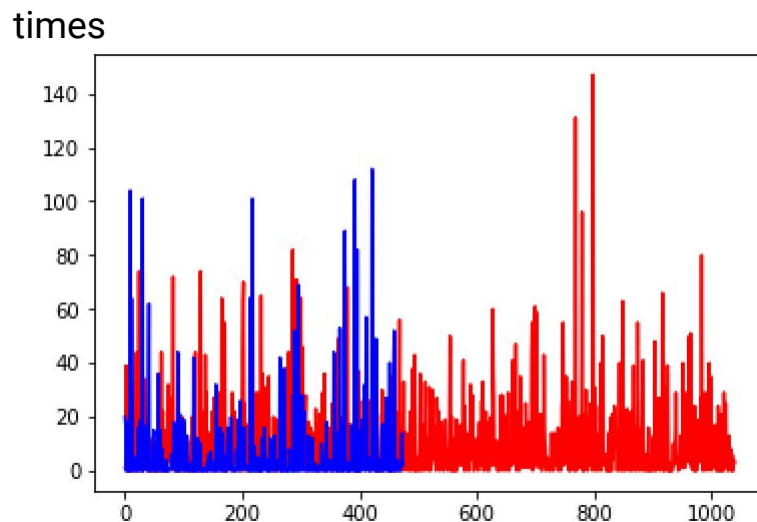
— People who did not purchase

— People who purchased

Internet banking



Credit card

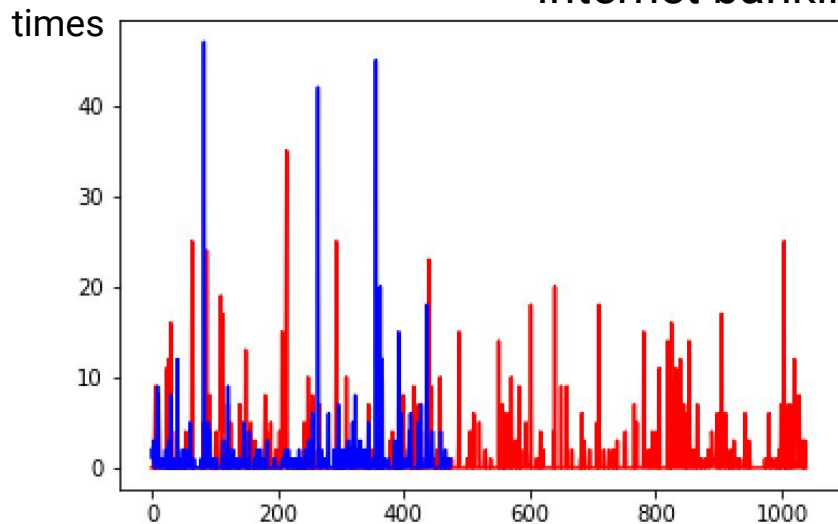


# Transaction?

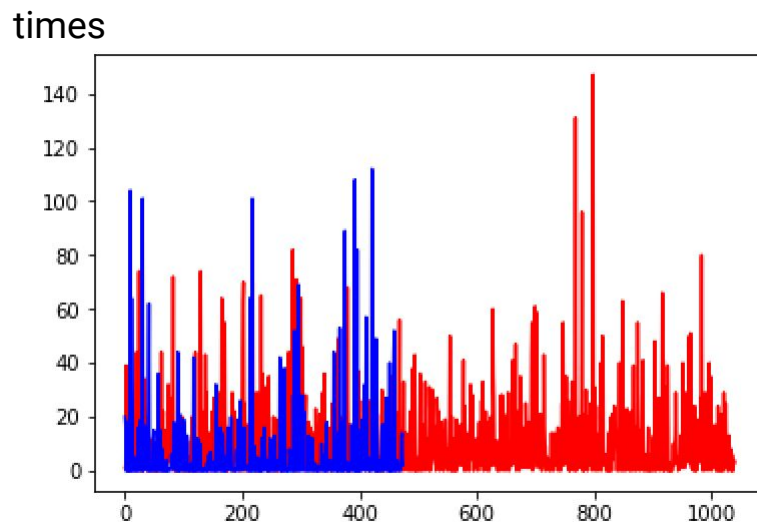
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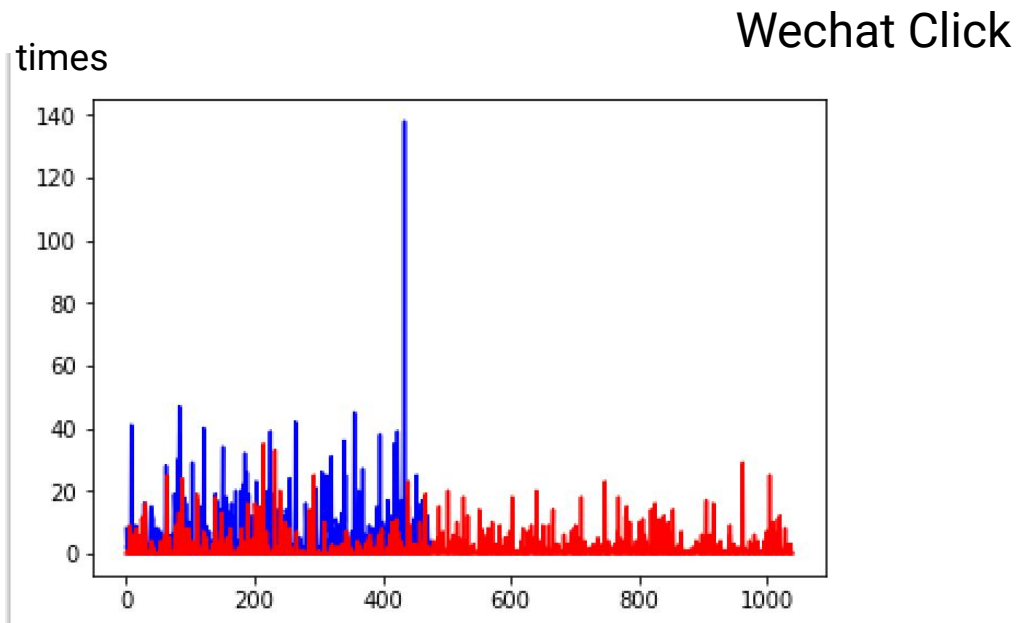


Not very helpful

# Transaction?

— People who did not purchase

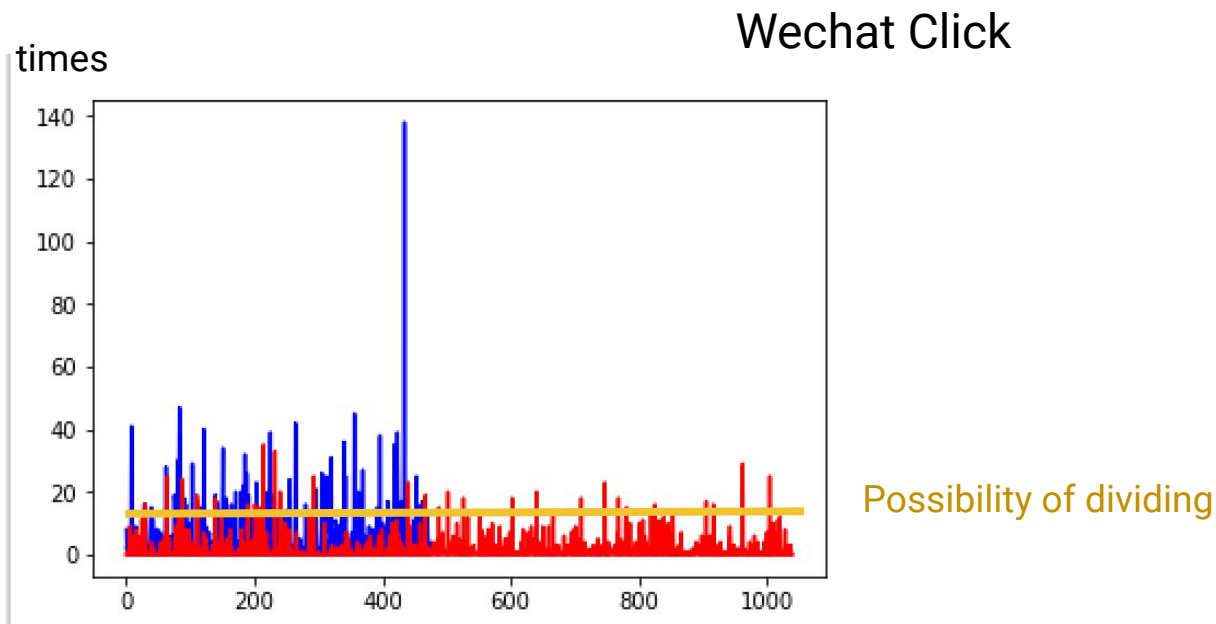
— People who purchased



# Transaction?

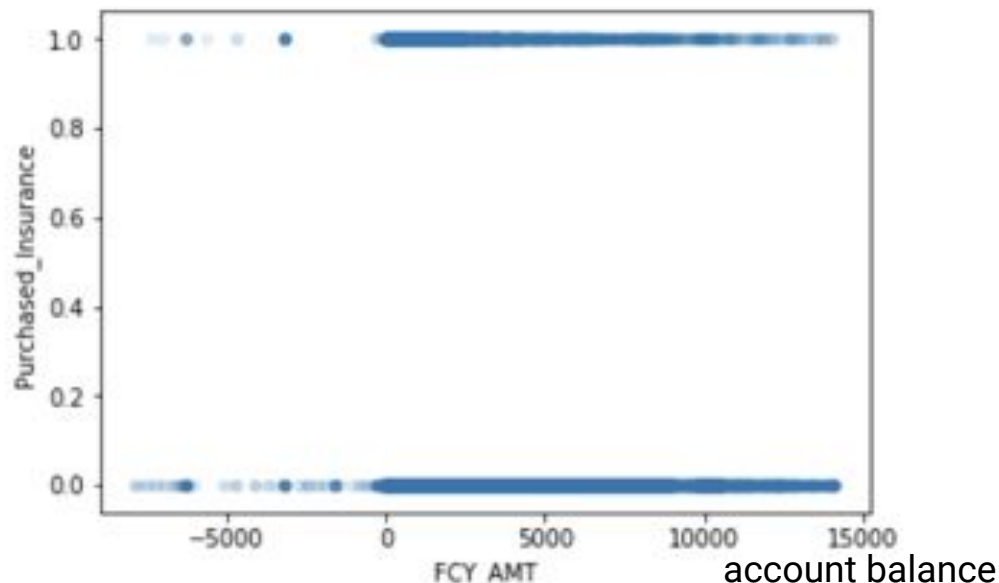
— People who did not purchase

— People who purchased



# Account Balance

whether they purchased (0/1)



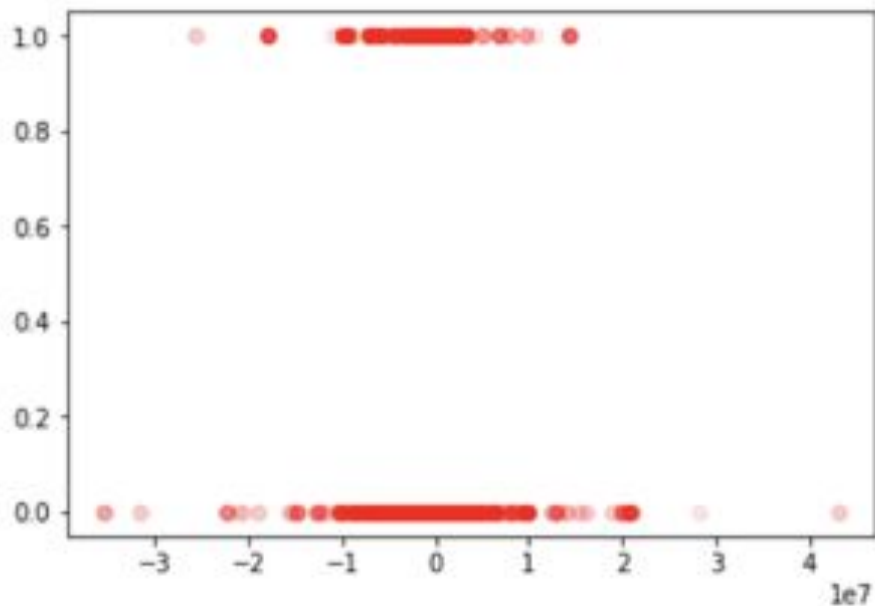
## Intuition:

- People with a negative balance are unlikely to purchase a wealth product.



# Change in Account Balance

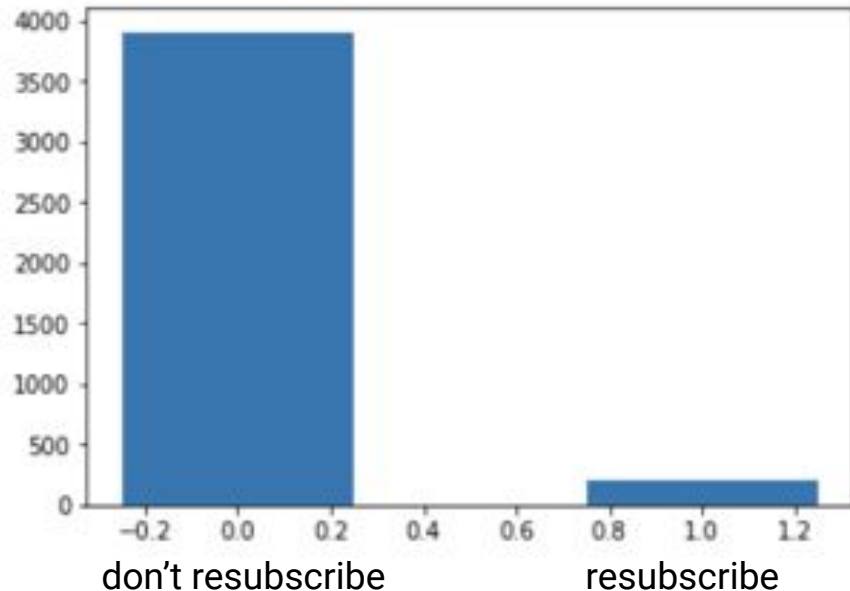
whether they purchased (0/1)



## Intuition:

- People with a relatively constant balance are the likeliest to make wealth purchases.

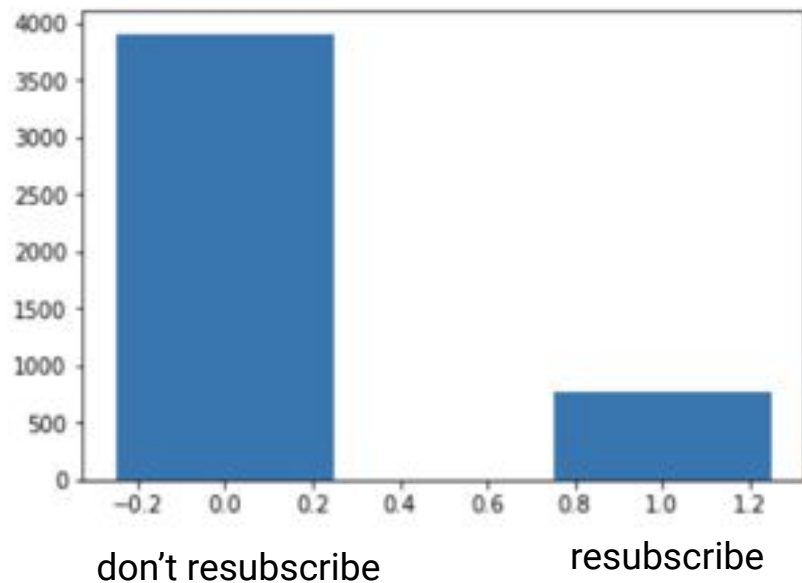
# TMD Expiration



## Intuition:

- Of the 4,000 customers whose TMD expired, only about 5% purchase a wealth product within the next three months.
- **Not useful**

# TMD Expiration – how about next year?



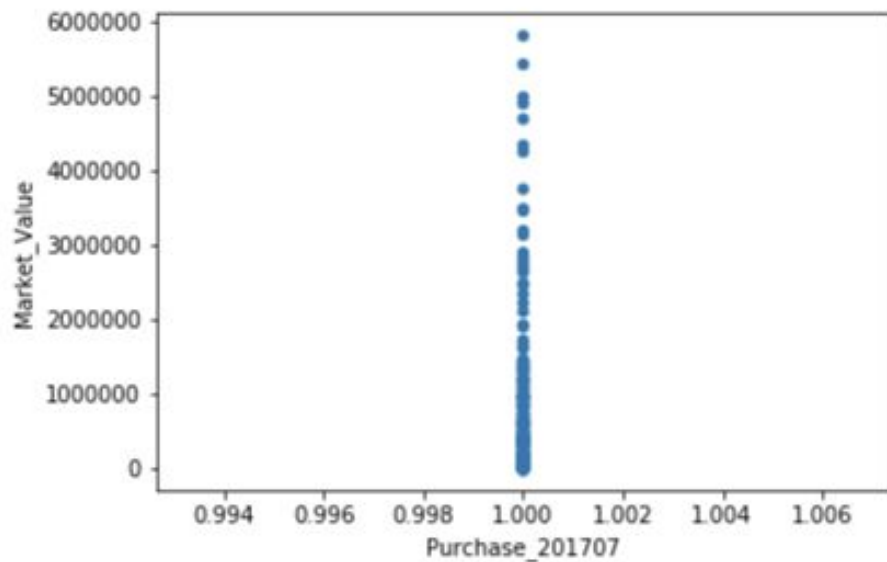
## Intuition:

- Of the 4,000 customers whose TMD expired, only about 20% purchase a wealth product within the next year.
- **Not useful also**

# More insights in resubscription

Why do only 20% of customers reinvest in HSBC?

market value of previous insurance

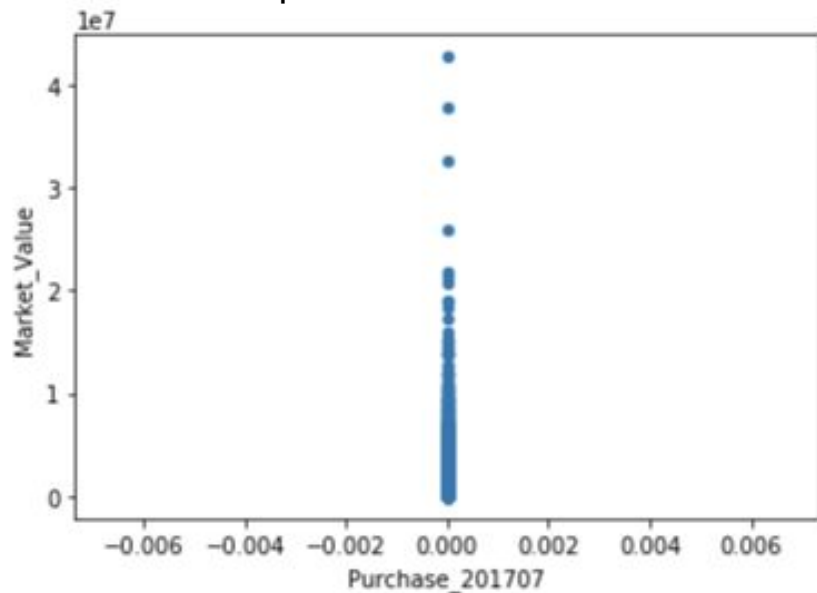


**Market Value of  
Customer's Insurance &  
Investment a month prior  
to **resubscription**.**

# More insights in resubscription

Why do only 20% of customers reinvest in HSBC?

market value of previous insurance

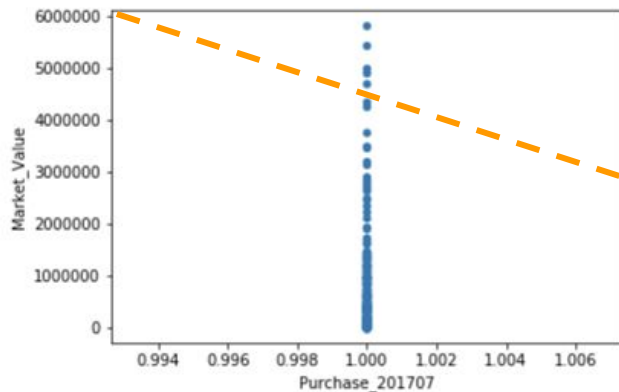


**Market Value of  
Customer's Insurance &  
Investment a month prior  
to **not resubscribing**.**

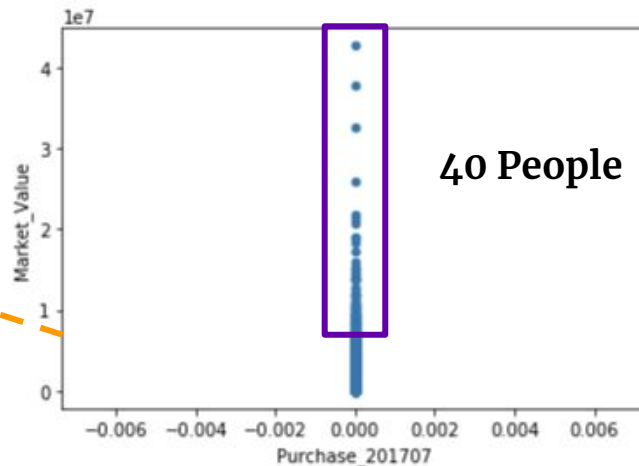
# More insights in resubscription

Why do only 20% of customers reinvest in HSBC?

**resubscribe**



**don't resubscribe**



So now we have gained some useful intuitions in pairwise features, it's time to train a neural network.....

Before that, we are taking into account the data with the strongest correlation: previous purchases



The best measure we could find of whether someone is going to purchase a wealth product is if they purchased one in the past. Leveraging this data we can probably get a far better prediction.

500999801104896		0		0		0		0		0		1		0		0		1		0		0		0
500999800909269		0		0		0		0		0		0		1		0		0		0		0		0
500999801050439		0		0		0		0		0		0		0		1		0		0		0		0
500999800637274		0		0		0		0		0		0		0		1		0		0		0		0
500999800860166		0		0		1		0		0		1		0		0		0		0		0		0
500999800159173		0		0		1		0		0		0		1		0		0		0		0		0
500999800519798		0		0		0		0		0		0		0		0		0		0		0		0
500999800733232		0		0		1		0		1		0		0		0		1		0		0		0
500999800744795		0		0		1		0		0		0		0		0		0		0		0		0
500999800765170		0		0		1		0		0		0		0		1		0		0		0		0
500999800438290		0		0		0		0		0		1		0		0		0		0		0		0
500999801028232		0		0		1		0		0		0		0		0		0		0		0		0
500999800455348		0		0		0		0		0		0		0		0		0		0		0		0
500999801101078		0		0		1		1		1		0		0		0		1		0		0		0
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500999800639073		0		0		1		1		1		0		1		0		0		1		0		0
500999800998986		0		0		1		0		0		0		0		0		0		0		0		0
500999800969192		0		0		0		0		0		1		0		0		0		0		0		0
500999800740393		0		0		0		0		0		0		1		0		0		0		0		0
500999800909089		0		0		0		0		0		0		1		0		0		0		0		0

# Finally, a neural network

age ●

gender ●

account balance ●

change ●

TMD Expiration ●

bought in  
2017/9 ●

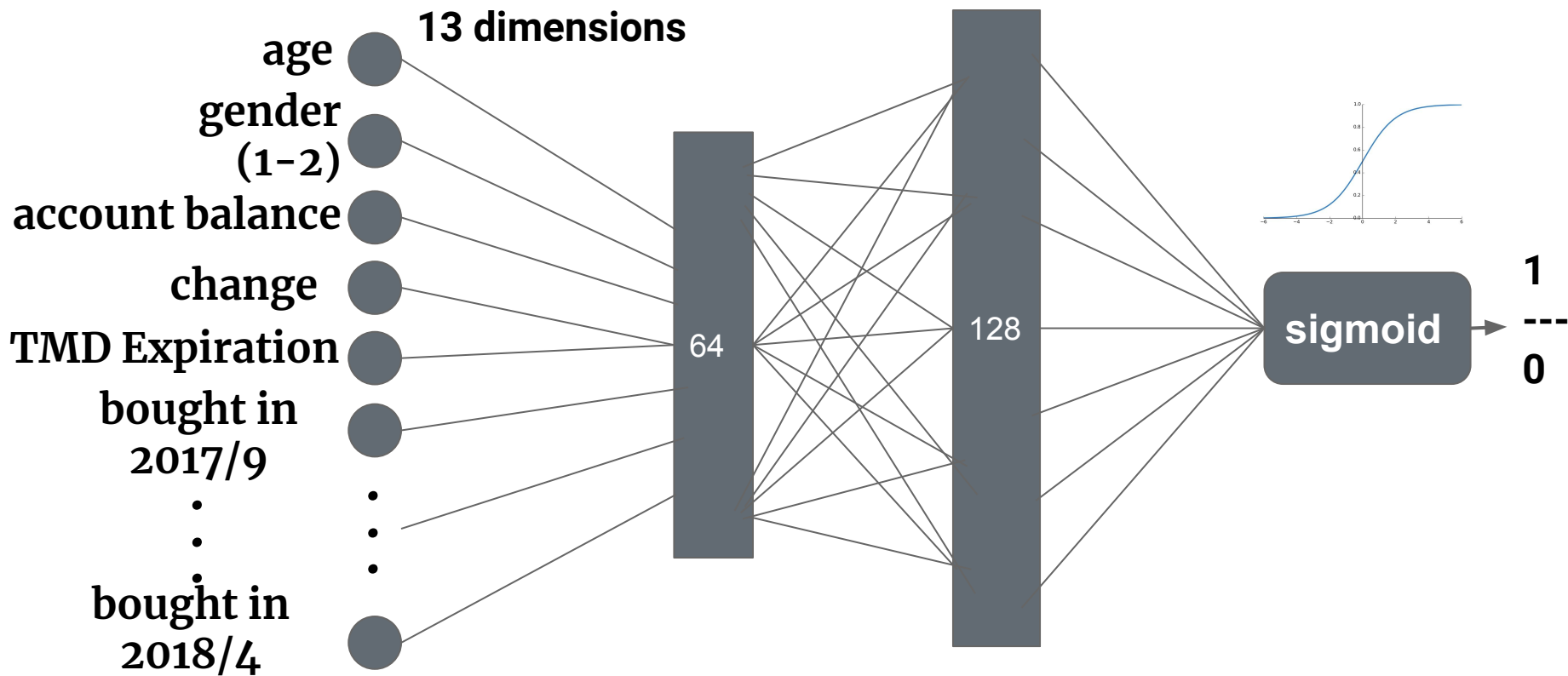
⋮  
⋮

bought in  
2018/4 ●

# Finally, a neural network

age	●	45
gender	●	1
account balance	●	3000000
change	●	-200000
TMD Expiration	●	1
bought in 2017/9	●	1
⋮	⋮	0
⋮	⋮	0
⋮	⋮	1
bought in 2018/4	●	0
	●	1
	●	0

# Finally, a neural network



# Training

We provide the randomly rescaled training set to avoid problem of unbalanced data.

# Training

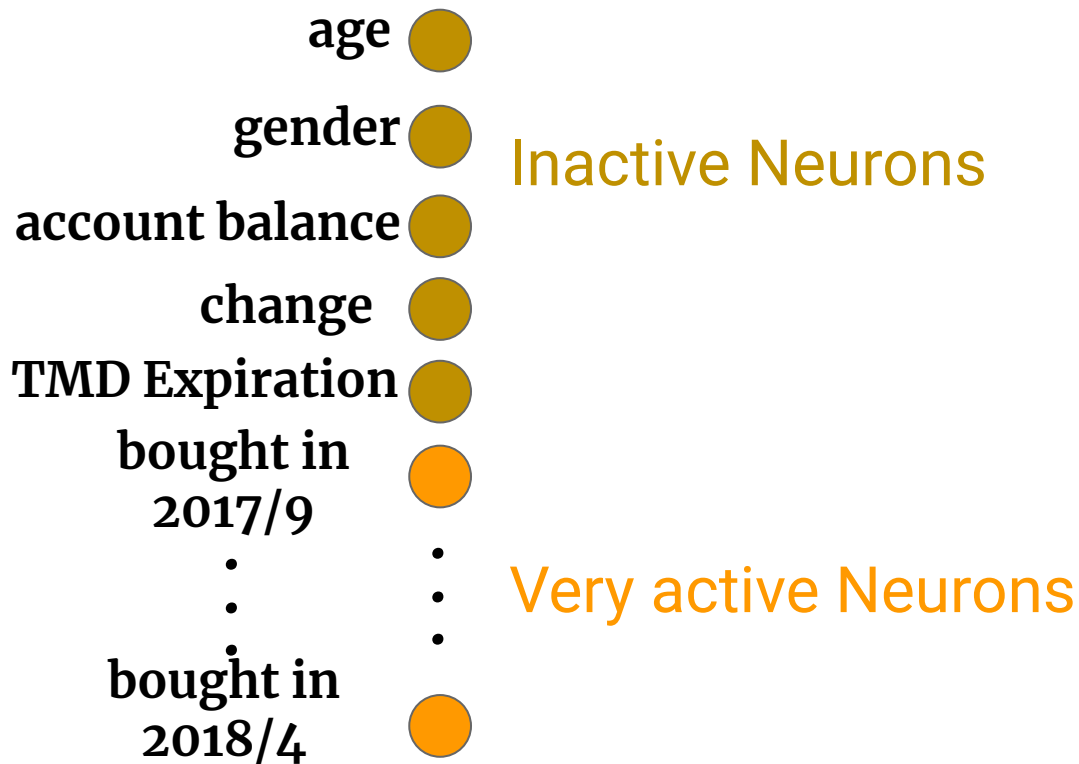
We provide the randomly rescaled training set to avoid problem of unbalanced data. The best case validation accuracy is 56%.

# Test error

The model will provide around 0.6% of predictions of 1.

In our testset, 473 are accurately predicted with the correct amount to be 2769

# What the problem might be?



## Potential problems:

- unbalanced dataset
- Inactive neurons (very small weight)
- The program cannot meet a satisfying training error

# Future Improvements

- As we do find some very useful pairwise connection with people who purchased and not, we believe a model with promising accuracy is highly possible
- More dimensions of data
- A bigger network
  - or possibly, a better network



# Final Prediction

- Our final prediction is based on the previous neural network which generates around 2000 customers
- We change the threshold a bit lower, which enlarges our final prediction to around 3000.
- Finally, we use pairwise connections to eliminate around 300 customers (eliminate people who have had high market values in wealth purchases)

Thank You!