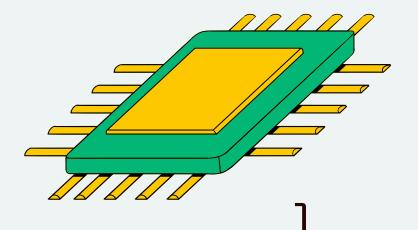


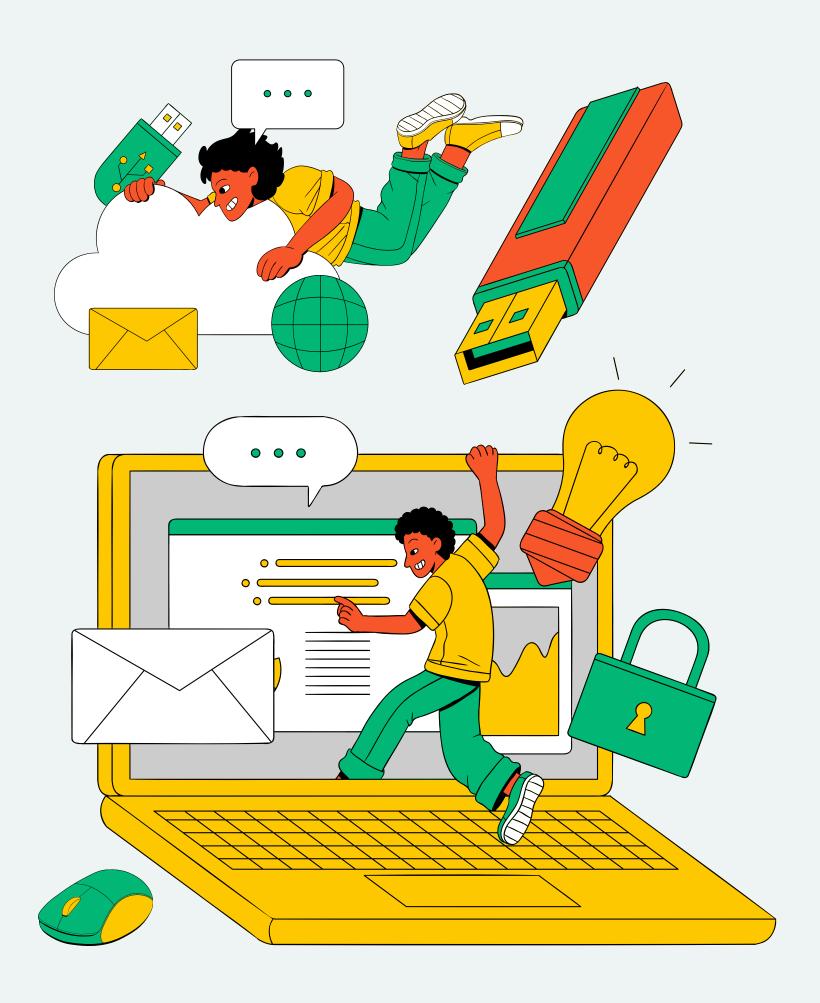
TRAFFIC PREDICTION

USING LOGISTIC REGRESSION

PRESENTED BY:

JIRATCHAYA PANPHINIJ 6310400941





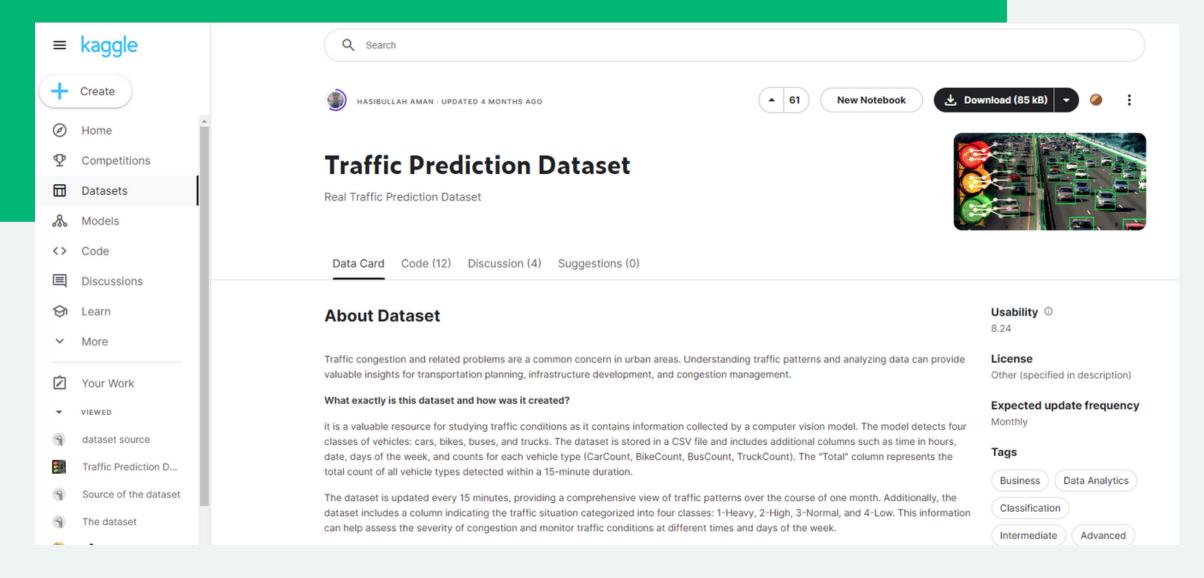
PRESENTATION OUTLINE

- Dataset
- Preprocessing Data
- Training
- Testing



DATASET

Afghanistan, Kabul, Abdul-haq Crossroad







DATASET

Time : Time

Day of the week : Monday, Tuesday, Wednesday,

Thursday, Friday, Saturday, Sunday

CarCount : NumberBikeCount : NumberBusCount : NumberTruckCount : NumberTotal : Number

Traffic Situation : low, nurmal, high, heavy



	Time	Day of the week	CarCount	BikeCount	BusCount	TruckCount	Total	Traffic Situation
0	12:00:00 AM	Tuesday	13	2	2	24	41	normal
1	12:15:00 AM	Tuesday	14	1	1	36	52	normal
2	12:30:00 AM	Tuesday	10	2	2	32	46	normal
3	12:45:00 AM	Tuesday	10	2	2	36	50	normal
4	1:00:00 AM	Tuesday	11	2	1	34	48	normal



PREPROCESSIONG DATA

	Time	Day of the week	CarCount	BikeCount	BusCount	TruckCount	Total	Traffic Situation
0	12:00:00 AM	Tuesday	13	2	2	24	41	normal
1	12:15:00 AM	Tuesday	14	1	1	36	52	normal
2	12:30:00 AM	Tuesday	10	2	2	32	46	normal
3	12:45:00 AM	Tuesday	10	2	2	36	50	normal
4	1:00:00 AM	Tuesday	11	2	1	34	48	normal

	Time	Day of the week	CarCount	BikeCount	BusCount	TruckCount	Total	Traffic Situation
0	0	2	13	2	2	24	41	0
1	0	2	14	1	1	36	52	0
2	0	2	10	2	2	32	46	0
3	0	2	10	2	2	36	50	0
4	1	2	11	2	1	34	48	0



PREPROCESSIONG DATA

SPLIT TRAIN AND TEST DATA

from sklearn.model_selection import train_test_split x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.2)

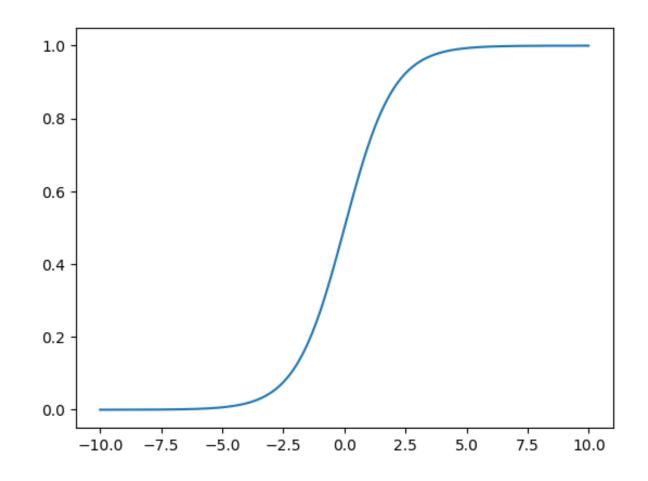
Training 80%

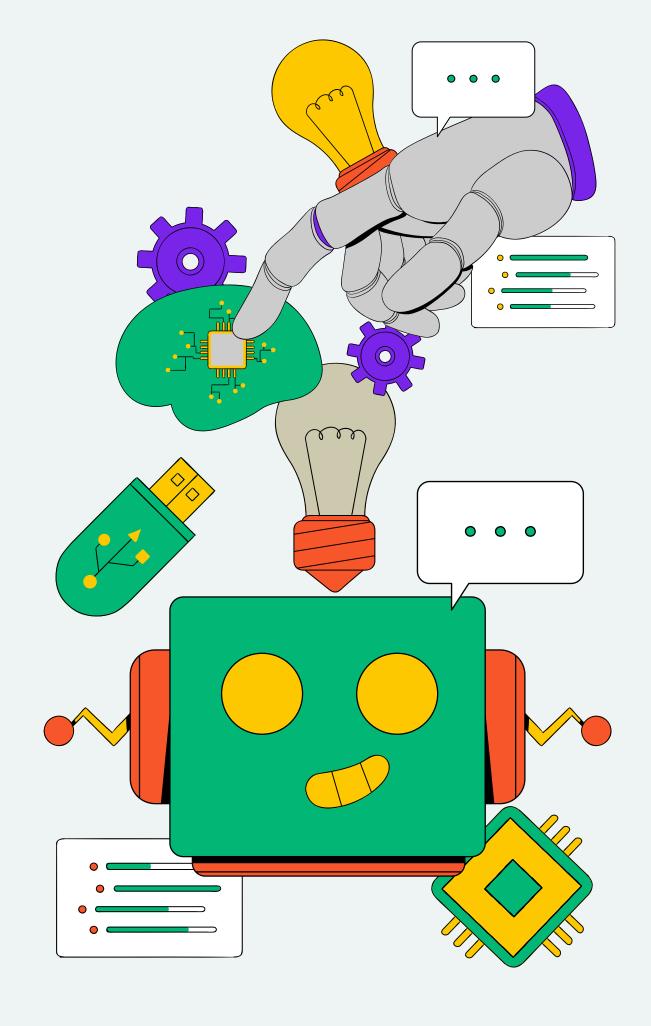
Test 20%



SIGMOID FUNCTION

$$P(y|x) = \frac{1}{1 + e^{-(w^T x + b)}}$$





LOSS FUNCTION: BINARY CROSS ENTROPY

$$h_{w,b}(x) = \frac{1}{1 + e^{-(w^T x + b)}}$$

$$J(w,b) = -\frac{1}{n} \sum_{i=1}^{n} \left[y_i \log \left(h_{w,b}(x_i) \right) + (1 - y_i) \log \left(1 - h_{w,b}(x_i) \right) \right] + \frac{\lambda}{2} \sum_{j=1}^{d} |w_j|^2$$

def sigmoid(self, z):

return 1/(1+np.exp(-z))

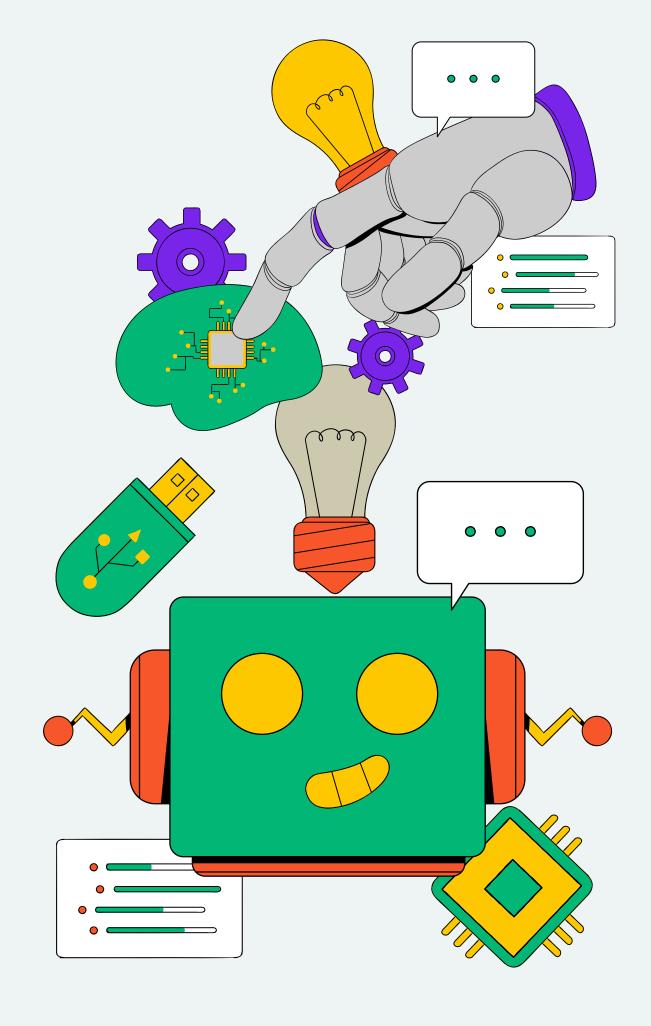
def cross_entropy(self, x, y):

eps = le-15 # Small constant value to prevent division by zero

z = np.dot(self.w, x.T) + self.b

y_pred = self.sigmoid(z)

 $return - (np.dot(y.T,np.log(y_pred + eps)) + np.dot((1-y).T,np.log(1-y_pred + eps)))/x.shape[O] + self.c*np.sum(np.square(self.w))/(2*x.shape[1])$

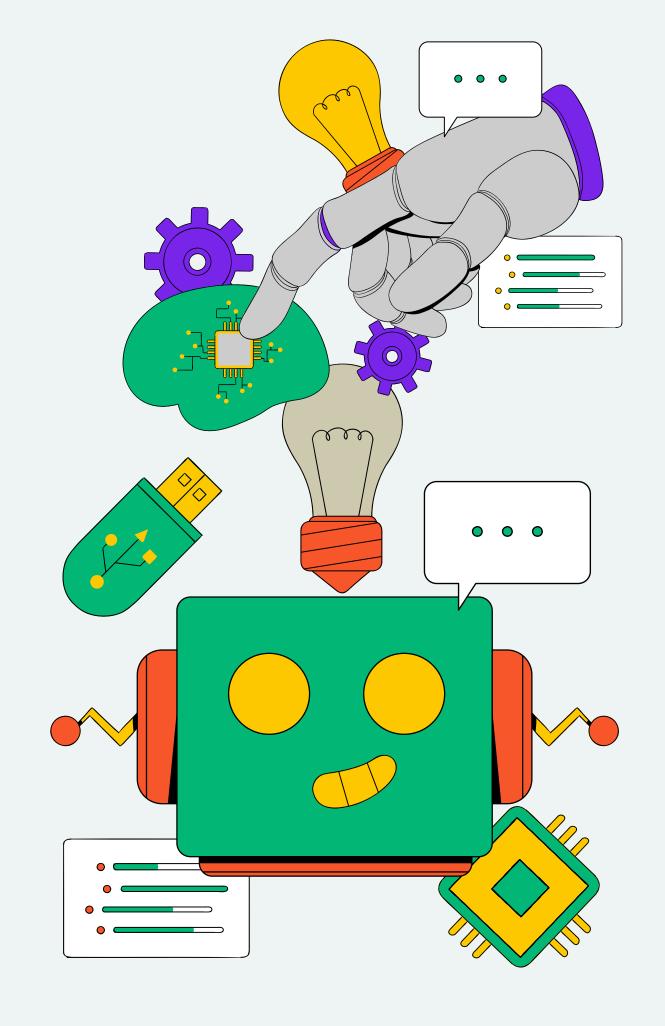


GRADIENT DESCENT

$$h_{w,b}(x) = \frac{1}{1 + e^{-(w^T x + b)}}$$

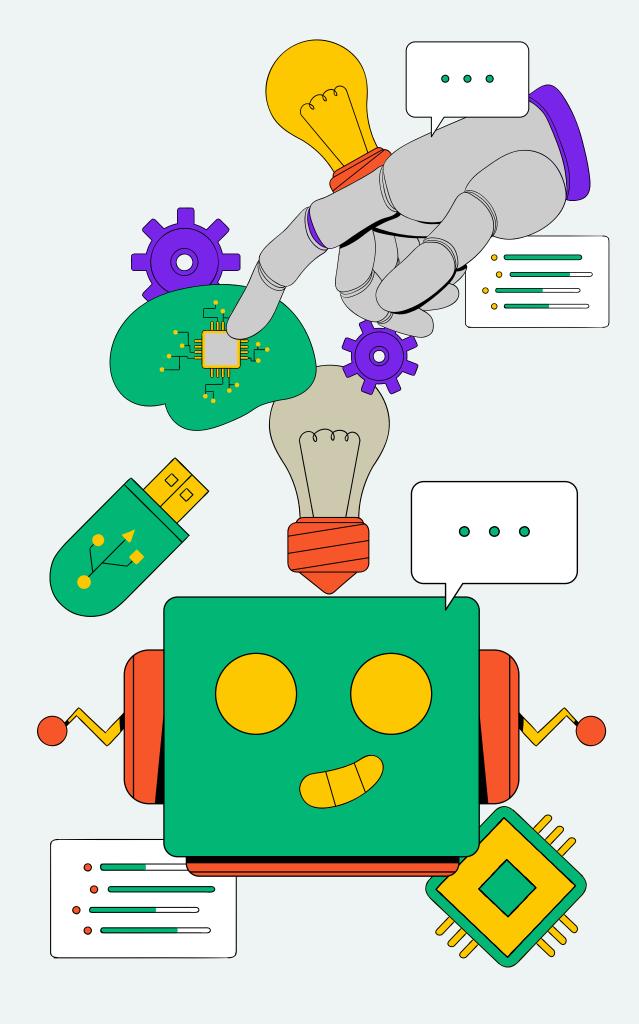
$$\frac{\partial}{\partial w_j} J(w, b) = \frac{1}{n} \sum_{i=1}^n \left[\left(h_{w, b}(x_i) - y_i \right) x_i^j \right] + \lambda w_j$$

$$\frac{\partial}{\partial b}J(w,b) = \frac{1}{n}\sum_{i=1}^{n}(h_{w,b}(x_i) - y_i)$$

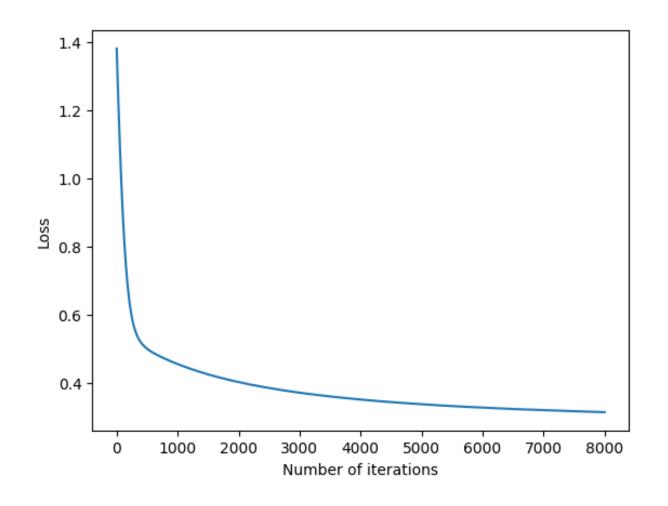


GRADIENT DESCENT

```
for i in range(self.iteration):
 # Random training data
 idx = np.random.choice(num_samples, int(batch_size*num_samples))
 x_batch = x.iloc[idx]
 y_batch = y[idx]
 # Predict
 z = np.dot(self.w, x_batch.T) + self.b
 y_pred = self.sigmoid(z)
 # Calculate gradient
 gred_w = np.dot(x_batch.T, (y_pred - y_batch))/num_samples
 gred_b = np.sum(y_pred - y_batch)/num_samples
 # Regularization
 gred_w = gred_w + self.c*self.w
 # Update parameter
 self.w = self.w - (self.learning_rete*gred_w)
 self.b = self.b - (self.learning_rete*gred_b)
```



clf = LogisticRegression(iteration=8000, learning_rete=0.01, c=0.01, penalty='l2')
clf.fit(x_train, y_train, batch_size=0.8)

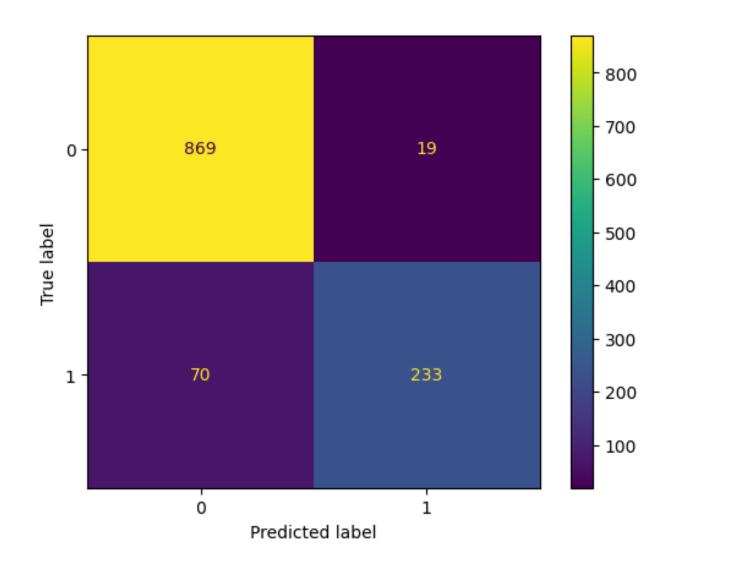


accuracy: 0.92

loss: 0.31

TESTING

accuracy: 0.92





THANK YOU

