Advanced techniques

Practice Session 4

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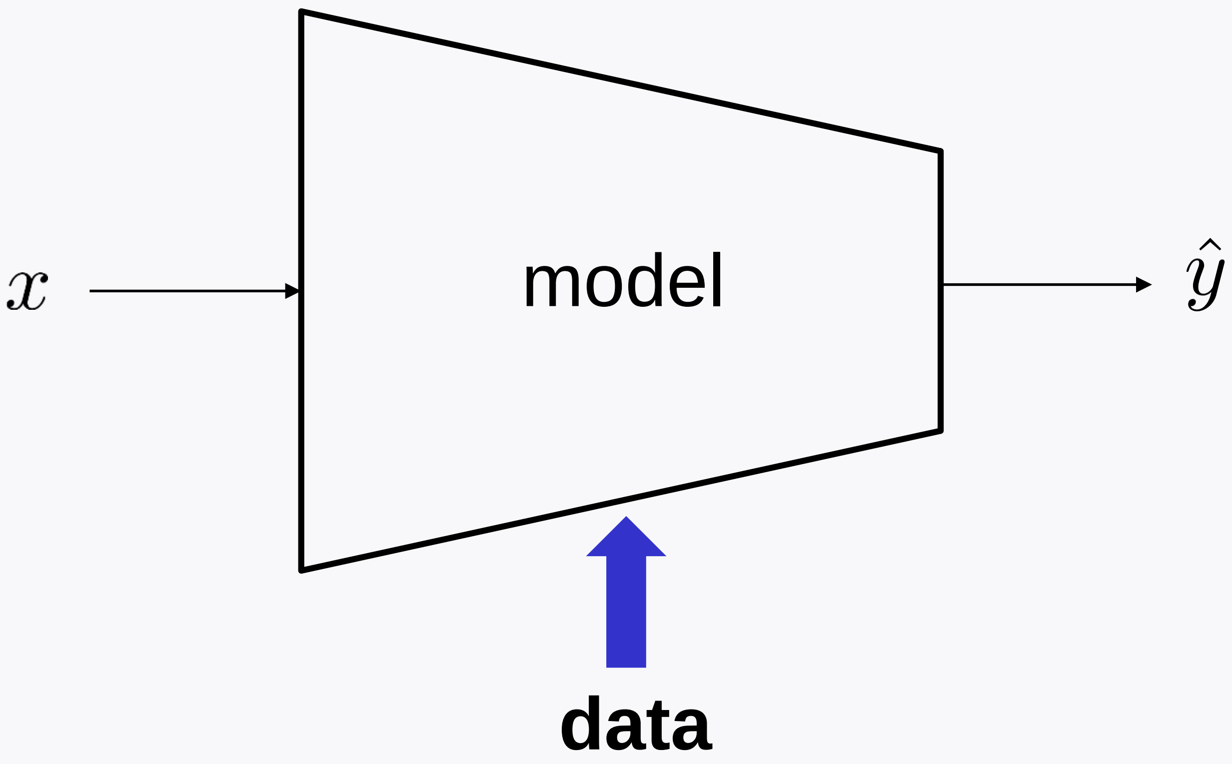
January 23, 2024

Recap: Machine learning



Recap: Training via optimization

Optimization problem:

$$\min_{w} \sum_{i=1}^{m} \ell(y^{(i)}, f_w(x^{(i)}))$$

Two things to choose:

1. loss function $\ell(\cdot)$ $\longrightarrow$ squared error loss
   cross entropy loss

2. model $f_w(\cdot)$ $\longrightarrow$ Perceptron
   DNN

Recap: How to solve?

$$\min_{w} \sum_{i=1}^{m} \ell(y^{(i)}, f_w(x^{(i)}))$$

Gradient descent:

$$w^{(t+1)} \leftarrow w^{(t)} - \alpha \boxed{\nabla J(w^{(t)})}$$

backpropagation

A prominent variant of gradient descent:

Adam

Recap: Data organization

m is a deciding factor for the **ratio** of data split:

4 regimes: Small, middle, large and ultra-large

val set dist. ~ test set dist. ~ target dist.

Recap: Generalization techniques

$$\min_{w} \sum_{i=1}^{m} \ell(y^{(i)}, f_w(x^{(i)})) \;\; +\lambda \|w\|^2$$

$$\boxed{\text{GD:} \;\; w^{(t+1)} \leftarrow w^{(t)} - \alpha \nabla J(w^{(t)})}$$

Generalization techniques

1. Regularization
2. Data augmentation
3. Early stopping
4. Dropout

Recap: Weight initialization

$$\min_{w} \sum_{i=1}^{m} \ell(y^{(i)}, f_w(x^{(i)}))$$

GD: $w^{(t+1)} \leftarrow w^{(t)} - \alpha \nabla J(w^{(t)})$

Question: How to choose $w^{(0)}$?

1. Xavier's initialization

2. He's initialization (under ReLU)

Recap: Techniques for training stability

$$\min_{w} \sum_{i=1}^{m} \ell(y^{(i)}, f_w(x^{(i)}))$$

GD: $$w^{(t+1)} \leftarrow w^{(t)} - \alpha \nabla J(w^{(t)})$$

1. Learning rate decaying

2. Batch normalization

Recap: Hyperparameter search

$$\min_{w} \sum_{i=1}^{m} \ell(y^{(i)}, f_w(x^{(i)}))$$

GD: $w^{(t+1)} \leftarrow w^{(t)} - \alpha \nabla J(w^{(t)})$

L of layers, # $n^{[\ell]}$ of hidden neurons, activation learning rate, betas, batch size, # *T* of epochs, regularization factor, dropout rate, …

Recap: Cross validation

4 fold cross validation:

val	train	train	train	test	val_1
train	val	train	train	test	val_2
train	train	val	train	test	val_3
train	train	train	val	test	val_4

Consider the average:

$$\text{val loss} = \frac{\text{val}_1 + \text{val}_2 + \text{val}_3 + \text{val}_4}{4}$$

Choose a hyperparameter that minimizes the **average loss.**

Outline

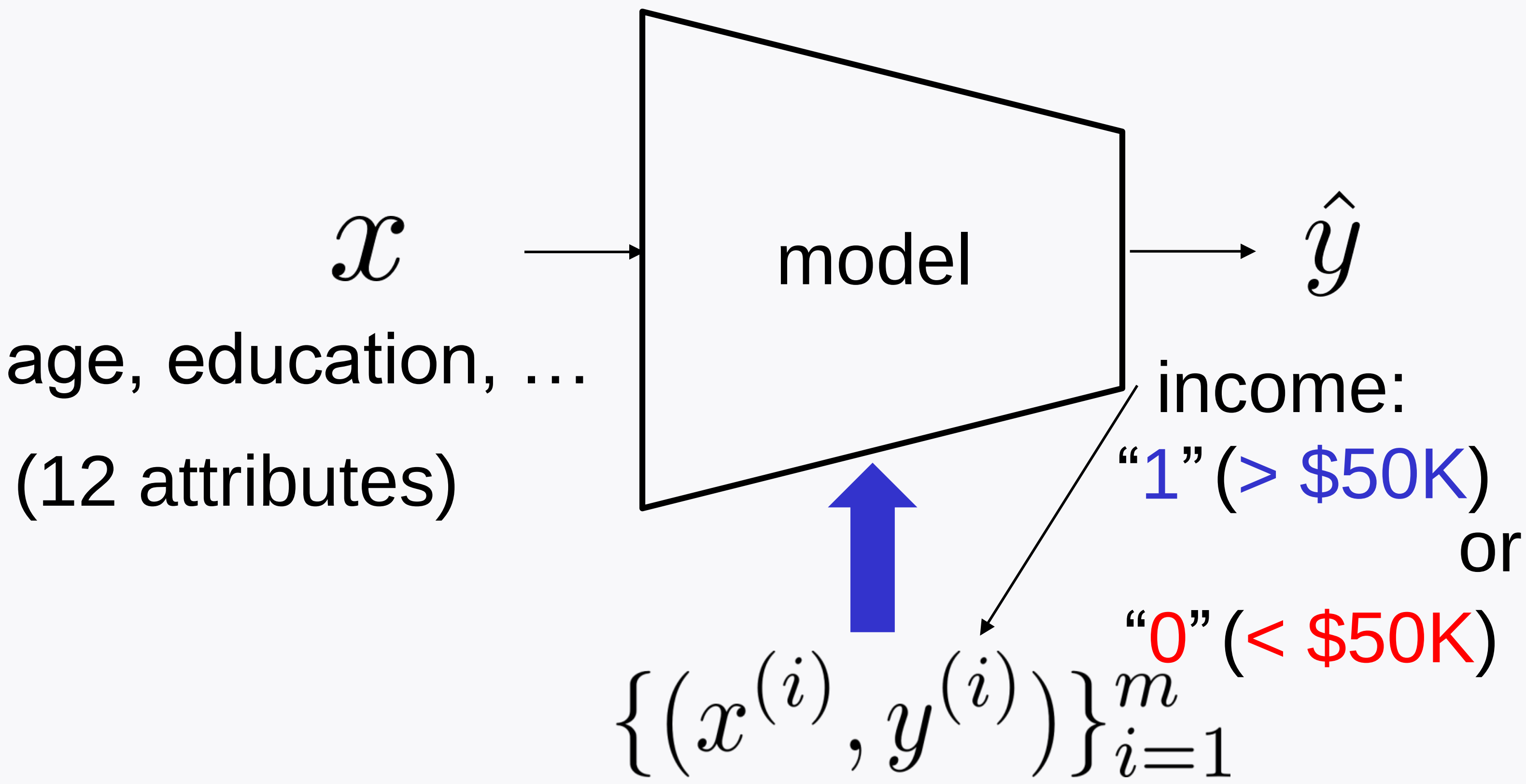
Will do coding exercises for all the techniques:

- Data organization (train/validation/test sets)
- Generalization techniques
- Weight initialization
- Techniques for training stability
- Hyperparameter search
- Cross validation

Will do this in the context of a simple task:

Adult income classification

Adult income classification



Data loading

```
pip install shap
```

```
from shap.datasets import adult
X, y = adult()
```

```
print(X.shape)
print(y.shape)
```

```
(32561, 12)
(32561,)
```

```
print(type(X))
print(type(y))
```

```
<class 'pandas.core.frame.DataFrame'>
<class 'numpy.ndarray'>
```

Data loading

```
pip install shap
from shap.datasets import adult
X, y = adult()
print(X)
print(y)
```

numerical data

Remaining is categorical

```
       Age  Workclass  Education-Num  Marital Status  Occupation
0      39.0          7           13.0               4           1
1      50.0          6           13.0               2           4
2      38.0          4            9.0               0           6
3      53.0          4            7.0               2           6
4      28.0          4           13.0               2          10
...     ...        ...            ...             ...         ...
32556  27.0          4           12.0               2          13
32557  40.0          4            9.0               2           7
32558  58.0          4            9.0               6           1
32559  22.0          4            9.0               4           1
32560  52.0          5            9.0               2           4
Relationship  Race  Sex  Capital Gain  Capital Loss  Hours per week  Country
           0     4    1        2174.0           0.0            40.0       39
           4     4    1           0.0           0.0            13.0       39
           0     4    1           0.0           0.0            40.0       39
           4     2    1           0.0           0.0            40.0       39
           5     2    0           0.0           0.0            40.0        5
         ...   ...  ...           ...           ...             ...      ...
           5     4    0           0.0           0.0            38.0       39
           4     4    1           0.0           0.0            40.0       39
           1     4    0           0.0           0.0            40.0       39
           3     4    1           0.0           0.0            20.0       39
           5     4    0       15024.0           0.0            40.0       39
[32561 rows x 12 columns]
```

```
[False False False ... False False  True]
```

Preprocessing

```
X, y = adult()
```

```
numerical_columns = ['Age','Education-Num','Capital Gain','Capital Loss','Hours per week']
categorical_columns = ['Workclass','Marital Status','Occupation','Relationship','Race','Sex','Country']
```

```
import pandas as pd # for one-hot encoding
```

```
from sklearn.preprocessing import StandardScaler # for normalization
```

```
# Normalization of numerical data
for column in numerical_columns:
    scaler = StandardScaler()
    X[column] = scaler.fit_transform(X[column].values.reshape(-1,1))
```

```
# Data type change of categorical data
for column in categorical_columns:
    X[column] = X[column].astype('category')
```

```
# One-hot encoding of categorical data
X = pd.get_dummies(X)
```

Preprocessing: data frame → numpy

```
# Conversion of data frame to numpy
X = X.values
```

```
# Converision: {False, True} --> {0., 1.}
y = y.astype(float)
```

```
print(X.shape)
print(y.shape)
print(y)
```

```
(32561, 50)
(32561,)
[0. 0. 0. ... 0. 0. 1.]
```

Data organization: train-val-test split

Suppose we want:

train:val:test = 8:1:1

to ensure the same distribution

```
from sklearn.model_selection import train_test_split
X_,X_test,y_,y_test = train_test_split(X,y,test_size=1/10,stratify=y)
X_train,X_val,y_train,y_val = train_test_split(X_,y_,test_size=1/9,stratify=y_)
```

```
print(X_train.shape)
print(X_val.shape)
print(X_test.shape)
```

```
(26048, 50)
(3256, 50)
(3257, 50)
```

```
print(sum(y_train)/y_train.shape)
print(sum(y_val)/y_val.shape)
print(sum(y_test)/y_test.shape)
```

```
[0.24082463]
[0.24078624]
[0.24071231]
```

Start with the simplest model

Logistic regression:

```
from sklearn.linear_model import LogisticRegression
```

```
model_LR = LogisticRegression()
```

```
# training
model_LR.fit(X_train, y_train)
```

```
# evaulation
val_acc = model_LR.score(X_val, y_val)
```

```
print(val_acc)
```

```
0.851044226044226
```

Saving a sklearn model

```
from joblib import dump

dump(model_LR, 'LR_sample.joblib')
```

☐	LR_sample.joblib	seconds ago	1.15 kB

Loading a saved model

```
from joblib import dump

dump(model_LR, 'LR_sample.joblib')
```

```
from joblib import load

loaded_model_LR = load('LR_sample.joblib')
```

Look ahead

Will apply many of the advanced techniques to improve performance.