

# Recitation #6

## CIS 519

CIS 519 TA Team

# Perceptron

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## Algorithm 1 Perceptron

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- 1: Initial weight vector:  $\mathbf{w}_1 = \mathbf{0} \in R^d$
  - 2: for  $t = 1 \rightarrow T$  do
  - 3:     Receive instance  $\mathbf{x}_t \in \mathbf{X} \subseteq R^d$
  - 4:     Predict  $\hat{y} = \text{sign}(\mathbf{w}_t^T \mathbf{x}_t)$
  - 5:     Receive true label  $y_t \in \{\pm 1\}$
  - 6:     Incur loss  $\mathbf{1}(\hat{y}_t \neq y_t)$
  - 7:     Update:
  - 8:     if  $\hat{y}_t \neq y_t$  then
  - 9:          $\mathbf{w}_{t+1} \leftarrow \mathbf{w}_t + y_t \mathbf{x}_t$
  - 10:     else
  - 11:          $\mathbf{w}_{t+1} \leftarrow \mathbf{w}_t$
  - 12:     end if
  - 13: end for
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# Winnow

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## Algorithm 2 Winnow

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```
1: Learning rate parameter  $\eta > 0$ 
2: Initial weight vector:  $\mathbf{w}_1 = (\frac{1}{d}, \dots, \frac{1}{d}) \in R^d$ 
3: for  $t = 1 \rightarrow T$  do
4:   Receive instance  $\mathbf{x}_t \in \mathbf{X} \subseteq R^d$ 
5:   Predict  $\hat{y} = \text{sign}(\mathbf{w}_t^T \mathbf{x}_t)$ 
6:   Receive true label  $y_t \in \{\pm 1\}$ 
7:   Incur loss  $\mathbf{1}(\hat{y}_t \neq y_t)$ 
8:   Update:
9:   if  $\hat{y}_t \neq y_t$  then
10:     for  $i = 1 \rightarrow d$  do
11:        $w_{t+1,i} \leftarrow \frac{w_{t,i} \exp(\eta y_t x_{t,i})}{Z_t}$ 
12:       where  $Z_t = \sum_{j=1}^n w_{t,j} \exp(\eta y_t x_{t,j})$ 
13:     end for
14:   else
15:      $\mathbf{w}_{t+1} \leftarrow \mathbf{w}_t$ 
16:   end if
17: end for
```

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# Perceptron with AdaGrad

$$g_t = \begin{cases} 0 & \text{if } y(w_t^\top x + \theta) > 1 \\ -y(x, 1) & \text{otherwise} \end{cases}$$

That is, for the first  $n$  features, that gradient is  $-yx$ , and for  $\theta$ , it is always  $-y$ .

Then, for each feature  $j$  ( $j = 1, \dots, n + 1$ ) we keep the sum of the gradients' squares:

$$G_{t,j} = \sum_{k=1}^t g_{k,j}^2$$

and the update rule is

$$w_{t+1,j} \leftarrow w_{t,j} - \eta g_{t,j} / (G_{t,j})^{1/2}$$

By substituting  $g_t$  into the update rule above, we get the final update rule:

$$w_{t+1,j} = \begin{cases} w_{t,j} & \text{if } y(w_t^\top x + \theta) > 1 \\ w_{t,j} + \eta y x_j / (G_{t,j})^{1/2} & \text{otherwise} \end{cases}$$

# Averaged Perceptron

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## Algorithm Averaged Perceptron

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- 1: **Training:**
  - 2: [m: #(examples); k: #(mistakes) = #(hypotheses);  $c_i$ : consistency count for  $v_i$  ]
  - 3: **Input:** a labeled training set  $(x_1, y_1), \dots, (x_m, y_m)$ , Number of epochs T
  - 4: **Output:** a list of weighted perceptrons  $(v_1, c_1), \dots, (v_k, c_k)$
  - 5: **Initialize:**  $k=0$ ;  $v_1 = 0$ ,  $c_1 = 0$
  - 6: **Repeat T times:**
  - 7: **for**  $t = 1 \rightarrow m$  **do**
  - 8:     Compute prediction  $\hat{y} = \text{sgn}(v_k \cdot x_i)$
  - 9:     **if**  $\hat{y} = y_i$  **then**
  - 10:          $c_k = c_k + 1$
  - 11:     **else**
  - 12:          $v_{k+1} = v_k + y_i x$
  - 13:          $c_{k+1} = 1$
  - 14:          $k = k + 1$
  - 15:     **end if**
  - 16: **end for**
  - 17: **Prediction:**
  - 18: **Given:** a list of weighted perceptrons  $(v_1, c_1), \dots, (v_k, c_k)$ , a new example x
  - 19: **Predict:** the label(x) as follows:
  - 20:  $y(x) = \text{sgn}[\sum_1^k c_i v_i \cdot x]$
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# Averaged Perceptron Implementation Details

- This average should be implemented by keeping only two weight vector. A cumulative weight vector computed during the training, and the current one.

# Understand the code

- Readers
- Perceptron Classifier
- Feature Extraction

# Real-world Reader

```
#Parse the real-world data to generate features,  
#Returns a list of tuple lists  
def parse_real_data(path):  
    #List of tuples for each sentence  
    data = []  
    for filename in os.listdir(path):  
        with open(path+filename, 'r') as file:  
            sentence = []  
            for line in file:  
                if line == '\n':  
                    data.append(sentence)  
                    sentence = []  
                else:  
                    sentence.append(tuple(line.split()))  
    return data
```



# Synthetic Reader 1

```
#Returns a list of labels
def parse_synthetic_labels(path):
    #List of tuples for each sentence
    labels = []
    with open(path+'y.txt', 'rb') as file:
        for line in file:
            labels.append(int(line.strip()))
    return labels
```

# Synthetic Reader 2

```
#Returns a list of features
def parse_synthetic_data(path):
    #List of tuples for each sentence
    data = []
    with open(path+'x.txt') as file:
        features = []
        for line in file:
            #print('Line:', line)
            for ch in line:
                if ch == '[' or ch.isspace():
                    continue
                elif ch == ']':
                    data.append(features)
                    features = []
            else:
                features.append(int(ch))
    return data
```

# Test Real-world Reader

- `email_dev_data = parse_real_data('Data/Real-World/Enron/dev/')`
- `news_dev_data = parse_real_data('Data/Real-World/CoNLL/dev/')`

# Test Synthetic Reader

- `syn_dense_dev_data = parse_synthetic_data('Data/Synthetic/Dense/dev/')`
- `syn_dense_dev_labels = parse_synthetic_labels('Data/Synthetic/Dense/dev/')`
- `syn_sparse_dev_data = parse_synthetic_data('Data/Synthetic/Sparse/dev/')`
- `syn_sparse_dev_labels = parse_synthetic_labels('Data/Synthetic/Sparse/dev/')`

# Perceptron Classifier

```
class Classifier(object):

    def __init__(self, algorithm, x_train, y_train, iterations=1, averaged = False, eta = 1, alpha = 1):

        # Get features from examples; this line figures out what features are present in
        # the training data, such as 'w-1=dog' or 'w+1=cat'
        features = {feature for xi in x_train for feature in xi.keys()}

        if algorithm == 'Perceptron':
            #Initialize w, bias
            self.w, self.w['bias'] = {feature:0.0 for feature in features}, 0.0
            #Iterate over the training data n times
            for i in range(iterations):
                #Check each training example
                for i in range(len(x_train)):
                    xi, yi = x_train[i], y_train[i]
                    y_hat = self.predict(xi)
                    #Update weights if there is a misclassification
                    if yi != y_hat:
                        for feature, value in xi.items():
                            self.w[feature] = self.w[feature] + yi*eta*value
                        self.w['bias'] = self.w['bias'] + yi*eta

    def predict(self, x):
        s = sum([self.w[feature]*value for feature, value in x.items()]) + self.w['bias']
        return 1 if s > 0 else -1
```

# Feature Extraction

```
# Feature extraction
print('Extracting features from real-world data...')
news_train_y = []
news_train_x = []
train_features = set([])
for sentence in news_train_data:
    padded = sentence[:]
    padded.insert(0, ('pad', None))
    padded.append(('pad', None))
    for i in range(1, len(padded)-1):
        news_train_y.append(1 if padded[i][1]=='I' else -1)
        feat1 = 'w-1='+str(padded[i-1][0])
        feat2 = 'w+1='+str(padded[i+1][0])
        feats = [feat1, feat2]
        train_features.update(feats)
        feats = {feature:1 for feature in feats}
        news_train_x.append(feats)
```

**Thanks!**