## NOISE CONTRASTIVE ESTIMATION

#### OUTLINE

- Rejection Sampling
- Logistic Regression
- Unsupervised as Supervised Learning
- Noise Contrastive Estimation
- Word 2 vec and negative sampling

## REJECTION SAMPLING

- JIV2 ares

## LOGISTIC REGRESSION

#### PROBLEM DEFINITION

#### Logistic regression seeks to

- Model the probability of an event occurring depending on the values of the independent variables, which can be categorical or numerical
- Estimate the probability that an event occurs for a randomly selected observation versus the probability that the event does not occur
- Predict the effect of a series of variables on a binary response variable
- Classify observations by estimating the probability that an observation is in a particular category (e.g. approved or not approved for a loan)

### **OUR DATA IN 1D**

PAY

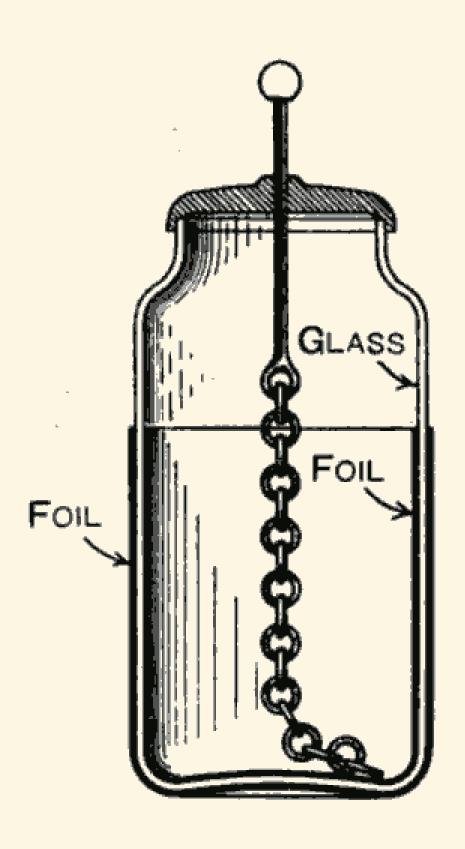
# BUT ALL I CAN DO IS FIT LINES?! ODDS LOG-ODDS

$$rac{p_+}{1-p_+}$$

Probability	Corresponding odds	
0.5	50:50 or 1	
0.9	90:10 or 9	
0.999	999:1 or 999	
0.01	1:99 or 0.0101	
0.001	1:999 or 0.001001	

$$\logigg(rac{p_+}{1-p_+}igg)$$

Log-odds	Probability	
0	0.5	
2.19	0.9	
6.9	0.999	
-4.6	0.01	
-6.9	0.001	

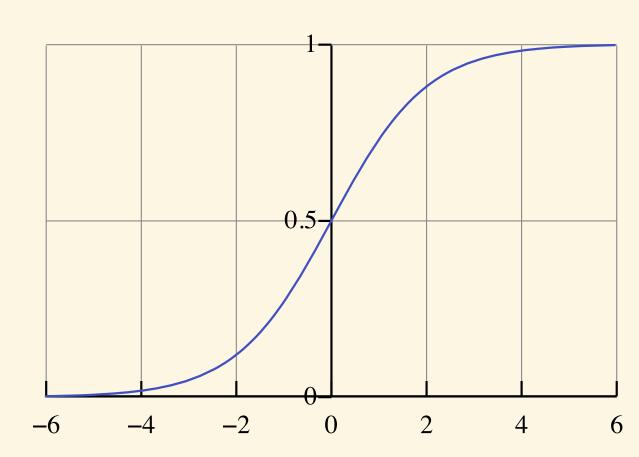


#### **LINEAR FIT TO LOG-ODDS**

$$egin{array}{ll} \log \left( rac{p_+}{1-p_+} 
ight) &= kx+b \ &= w_1x+w_0 \ &= \mathbf{w}^T\mathbf{x} \end{array}$$

#### WHAT'S THE PROBABILITY?

$$egin{aligned} \log\left(rac{p_+}{1-p_+}
ight) &= \mathbf{w}^T\mathbf{x} \ rac{p_+}{1-p_+} &= e^{\mathbf{w}^T\mathbf{x}} \ p_+ &= e^{\mathbf{w}^T\mathbf{x}}(1-p_+) \ p_+ &= e^{\mathbf{w}^T\mathbf{x}} - p_+ e^{\mathbf{w}^T\mathbf{x}} \ p_+ &+ p_+ e^{\mathbf{w}^T\mathbf{x}} &= e^{\mathbf{w}^T\mathbf{x}} \ p_+ &= rac{e^{\mathbf{w}^T\mathbf{x}}}{1+e^{\mathbf{w}^T\mathbf{x}}} \ p_+ &= rac{1}{1+e^{-\mathbf{w}^T\mathbf{x}}} \end{aligned}$$



#### WHAT'S THE PROBABILITY WHEN IT IS INTERESTING?

$$egin{aligned} \mathrm{P}(G=k|X=x) &= rac{e^{\mathbf{w}_k^T\mathbf{x}}}{1+\sum_i^{K-1}e^{\mathbf{w}_i^T\mathbf{x}}}, k=1,\ldots,K-1 \ \mathrm{P}(G=K|X=x) &= rac{1}{1+\sum_i^{K-1}e^{\mathbf{w}_i^T\mathbf{x}}} \end{aligned}$$

## SOFTMAX!

$$\sigma(\mathbf{z})_i = rac{e^{z_i}}{\sum_{j=1}^K e^{z_j}}$$

## AN ALTERNATIVE PERSPECTIVE ON LOG ODDS

What's posterior probability of class  $c_1$  given a sample  $\mathbf{x}$ ?

$$\mathrm{p}(c_1|\mathbf{x}) = rac{\mathrm{p}(\mathbf{x}|c_1)\mathrm{p}(c_1)}{\mathrm{p}(\mathbf{x}|c_1)\mathrm{p}(c_1) + \mathrm{p}(\mathbf{x}|c_2)\mathrm{p}(c_2)}$$

Let's introduce 
$$a=\ln rac{\mathrm{p}(\mathbf{x}|c_1)\mathrm{p}(c_1)}{\mathrm{p}(\mathbf{x}|c_2)\mathrm{p}(c_2)}$$

$$\mathrm{p}(c_1|\mathbf{x}) = rac{1}{1+\exp{(-a)}} = \sigma(a)$$

Nice properties of logistic sigmoid

$$\sigma(-a) = 1 - \sigma(-a)$$
  $a = \ln{(rac{\sigma}{1-\sigma})} \log{
m odds}??? \ rac{d\sigma}{da} = \sigma(1-\sigma)$ 

#### MAXIMUM LIKELIHOOD ESTIMATE

$$egin{aligned} l(\mathbf{w}) &= rg \max_{\mathbf{w}} \ \prod_{i}^{N} P_{\mathbf{w}}(c_{k}|x_{i}) \ & l(\mathbf{w}) &= rg \max_{\mathbf{w}} \ \prod_{i:\mathbf{x}_{i} \in c_{1}}^{N} P_{\mathbf{w}}(c_{1}|x_{i}) \prod_{i:\mathbf{x}_{i} \in c_{2}}^{N} P_{\mathbf{w}}(c_{2}|x_{i}) \ & l(\mathbf{w}) &= rg \max_{\mathbf{w}} \ \prod_{i:\mathbf{x}_{i} \in c_{1}}^{N} \sigma \prod_{i:\mathbf{x}_{i} \in c_{2}}^{N} (1-\sigma) \ & l(\mathbf{w}) &= rg \max \ \prod_{i}^{N} \sigma_{i}^{l_{1}} (1-\sigma_{i})^{1-l_{1}} \end{aligned}$$

#### **NEGATIVE LOG LIKELIHOOD**

$$egin{align} l(\mathbf{w}) &= rg \max_{\mathbf{w}} \ \prod_{i}^{N} \sigma_{i}^{l_{1}} (1 - \sigma_{i})^{1 - l_{1}} \ \ell(\mathbf{w}) &= - \sum_{i}^{N} (l_{i} \ln(\sigma_{i}) + (1 - l_{i}) \ln(1 - \sigma_{i})) \end{aligned}$$

## UNSUPERVISED AS SUPERVISED LEARNING

H.T.F. edition 009 - Second Section 14, 2.4 X, ··· XNo X, ... XN N+No 9(X) N+No (g(x)+g(x))/2g(x) $\frac{g_0(X)(y)}{g(x)} = p(y|x) = \frac{g(x)}{g(x)} + \frac{g_0(x)}{g(x)}$  $= Tg_0(x) g(x) = g_0(x) T_{-M}(x)$ 

## NOISE CONTRASTIVE ESTIMATION

14.2.4  $27201(x_t;\theta)]+00[1-h$ h(u;0) = 1+e(-6(u;0) In Pm(4; b)-1

Pm(4; b)-1

Pm(4; b)-1

Pm(4; b)-1  $G(u;\theta)$ 

## WORD2VEC AND NEGATIVE SAMPLING

