Logistic regression unit:

- Derivation from linear regression (last week Friday)
- Lab activity: Applying logistic regression (Monday)
- Multiclass classification (today)
- [Begin Gaussian mixture models unit (Friday)]

Today:

Correction/clarification of linear regression formulas

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- Warm-up: The derivative of the logistic function
- Training logistic regression
- Multiclass classification

[Original:] The closed form solution for plain old linear regression is

$$\boldsymbol{\theta}^{T} = (\mathbf{X}^{T}\mathbf{X})^{-1}\mathbf{X}^{T}\mathbf{y}$$

For ridge regression, it is

$$\boldsymbol{\theta}^{\mathsf{T}} = (\mathbf{X}^{\mathsf{T}}\mathbf{X} + \mathbf{A})^{-1}\mathbf{X}^{\mathsf{T}}\mathbf{y}$$

The mean square error:

$$\mathcal{L}_{MSE}(\boldsymbol{\theta}) = \frac{1}{N} || \boldsymbol{y}^{T} - \boldsymbol{\theta}^{T} \boldsymbol{X}^{T} ||^{2} = \frac{1}{N} || \boldsymbol{y} - \boldsymbol{X} \boldsymbol{\theta} ||^{2}$$

The gradient of this loss function:

$$abla_{m{ heta}} \mathcal{L} = rac{1}{N} (-2 m{y}^T m{X} + 2 m{ heta}^T m{X}^T m{X})$$

For ridge:

$$\begin{aligned} \mathcal{L}(\boldsymbol{\theta}) &= \frac{1}{N} || \boldsymbol{y}^{T} - \boldsymbol{\theta}^{T} \boldsymbol{X} ||^{2} + \alpha || \boldsymbol{\theta} ||^{2} \\ \nabla_{\boldsymbol{\theta}} \mathcal{L} &= \frac{1}{N} (-2 \boldsymbol{y}^{T} \boldsymbol{X} + 2 \boldsymbol{\theta}^{T} \boldsymbol{X}^{T} \boldsymbol{X}) + 2 \alpha \boldsymbol{\theta} \end{aligned}$$

For LASSO:

$$\mathcal{L}(\boldsymbol{\theta}) = \frac{1}{N} || \mathbf{y}^{T} - \boldsymbol{\theta}^{T} \mathbf{X} ||^{2} + \alpha || \boldsymbol{\theta} ||^{1}$$

$$\nabla_{\boldsymbol{\theta}} \mathcal{L} = \frac{1}{N} (-2\mathbf{y}^{T} \mathbf{X} + 2\boldsymbol{\theta}^{T} \mathbf{X}^{T} \mathbf{X}) + 2\alpha (\operatorname{sign}(\boldsymbol{\theta}_{i}))$$

[Fixed/clarified:] The closed form solution for plain old linear regression is

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$$\nabla_{\boldsymbol{\theta}} \mathcal{L} = \frac{1}{N} (-2 \boldsymbol{y}^{T} \boldsymbol{X} + 2 \boldsymbol{\theta}^{T} \boldsymbol{X}^{T} \boldsymbol{X}) + 1 \alpha (\operatorname{sign}(\boldsymbol{\theta}_{i}))$$

Model family for logistic regression (as a probability function):

$$p(\mathbf{x}) = \sigma(\boldsymbol{\theta}^{\mathsf{T}}\mathbf{x})$$

Loss function (*mean log loss*):

$$\mathcal{L}(\boldsymbol{\theta}) = -\frac{1}{N} \sum_{n=0}^{N-1} \left(y_n \ln \sigma(\boldsymbol{\theta}^T \boldsymbol{x_n}) + (1 - y_n) \ln(1 - \sigma(\boldsymbol{\theta}^T \boldsymbol{x_n})) \right)$$

Gradient of the mean log loss:

$$\nabla_{\boldsymbol{\theta}} \mathcal{L} = \frac{1}{N} \left[\cdots \sum_{n=0}^{N-1} x_{n,i} (\sigma(\boldsymbol{\theta}^{\mathsf{T}} \boldsymbol{x}_{n}) - y_{n}) \cdots \right]$$

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Score function for each class $k \in [0, K)$ (where K is the number of classes:

$$s_k(\mathbf{x}) = \mathbf{\theta}_{\mathbf{k}}^T \mathbf{x}$$

Softmax function $\sigma : \mathbb{R}^K \to [0,1]^K$ (this is a different $\sigma \dots$):

$$\sigma(\boldsymbol{z})_k = rac{e^{\boldsymbol{z}_k}}{\sum_{j=0}^{K-1} e^{\boldsymbol{z}_j}} ext{ for } k \in [0, K)$$

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Coming up:

Do gradient descent /linear regression assignment (due end-of-day Thurs, Feb 9)

Take logistic regression quiz (due classtime Fri, Feb 10)

Read textbook portions about probability and distributions (due end-of-day Mon, Feb 13)

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Do logistic regression assignment (due end-of-day Wed, Feb 15)

(Reading and response assignment forthcoming...)

Project dataset confirmation (due end-of-day Fri, Feb 17)