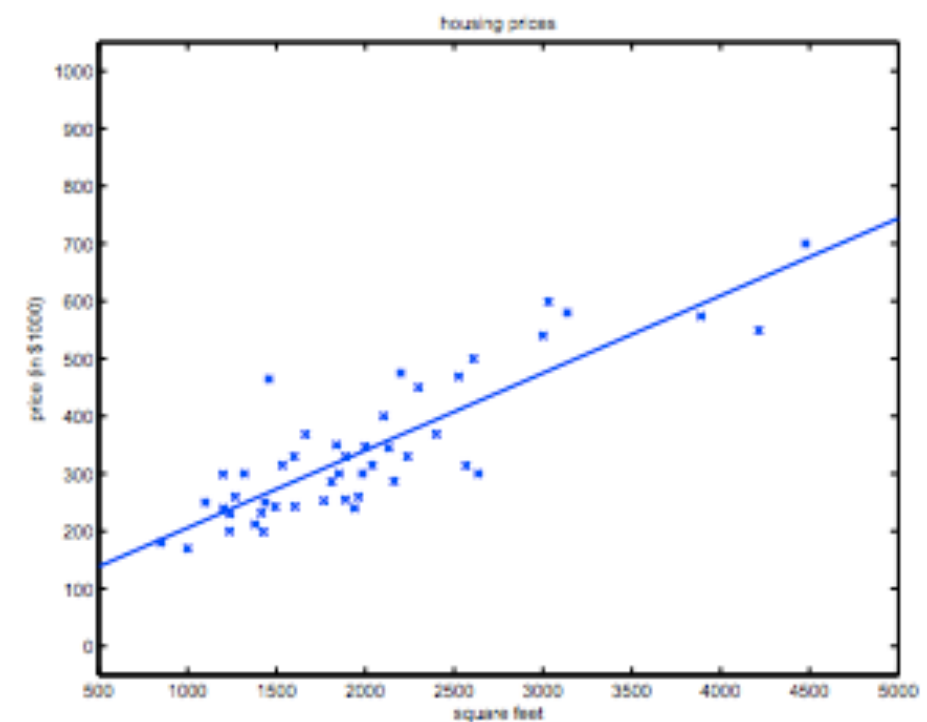
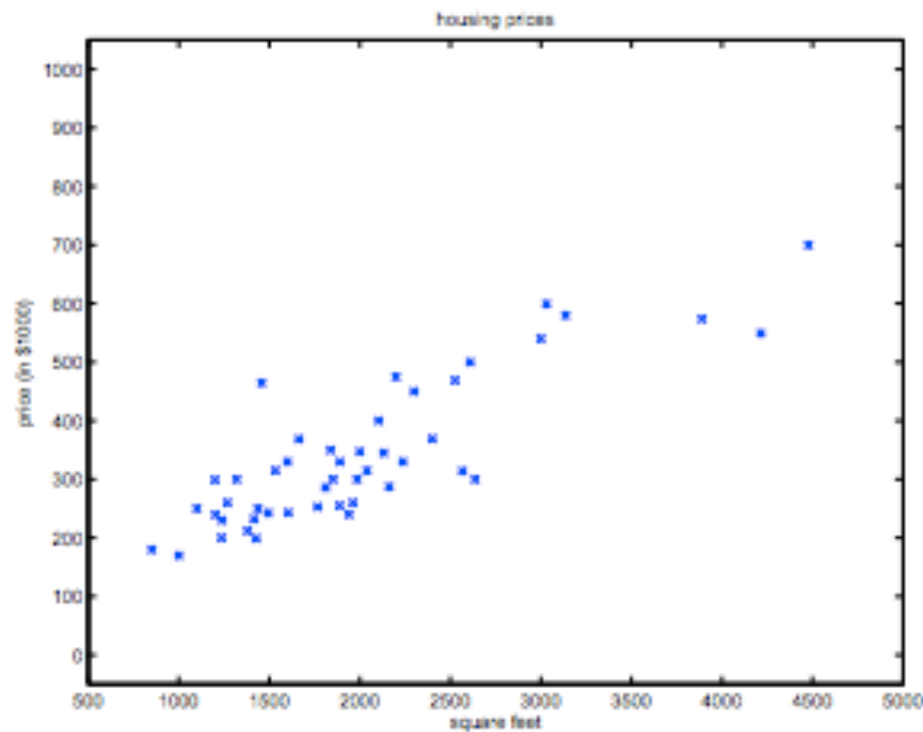
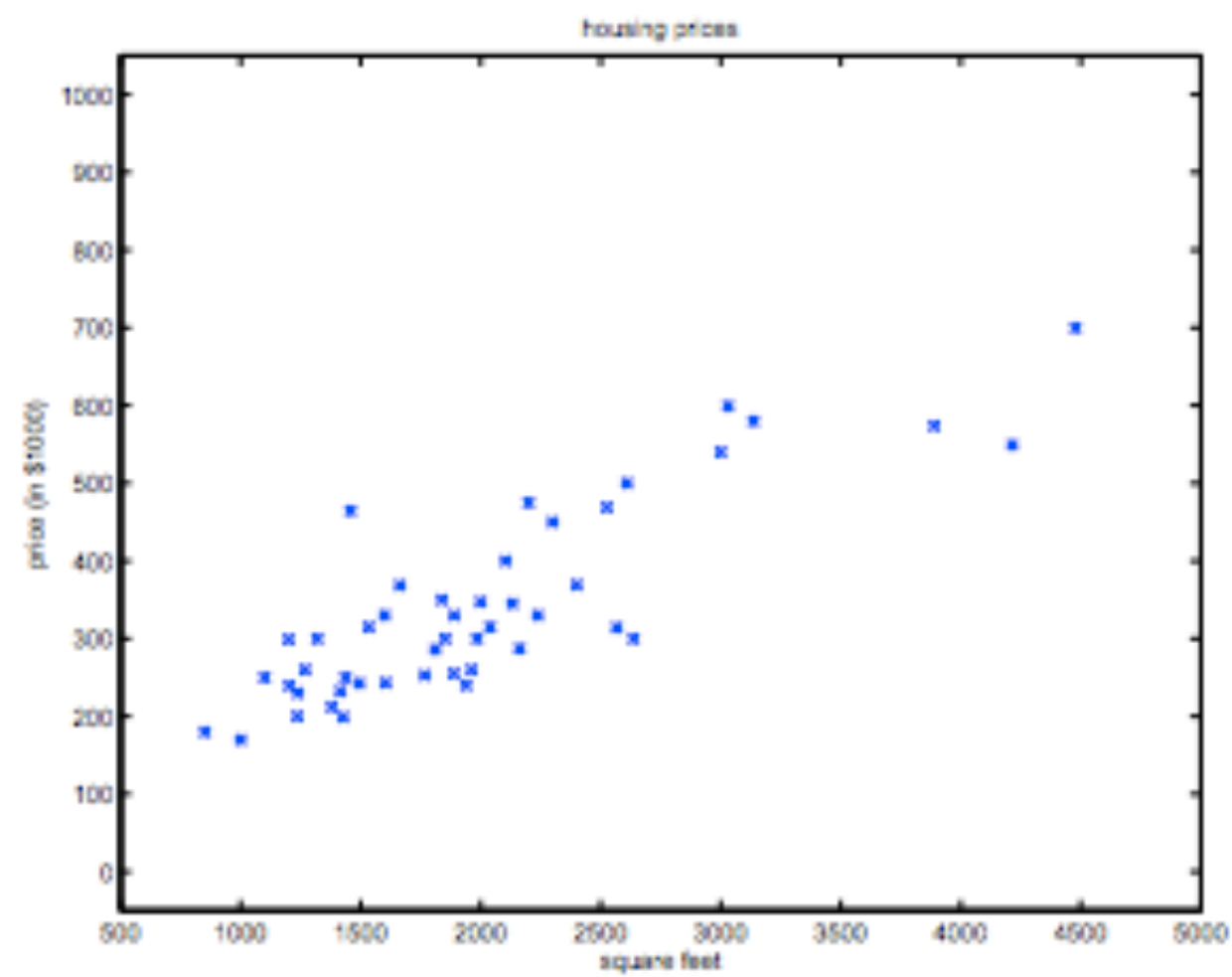


Linear Regression

Linear Reg Overview



- Examples? Counter-examples?
- Methodology?



General Multivariate Form

$$h_{\theta}(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2$$

$$h(x) = \sum_{i=0}^n \theta_i x_i = \theta^T x$$

Squared Error Loss

$$J(\theta) = \frac{1}{2} \sum_{i=1}^m (h_{\theta}(x^{(i)}) - y^{(i)})^2$$

Why?

Gradient Descent

$$\begin{aligned}\frac{\partial}{\partial \theta_j} J(\theta) &= \frac{\partial}{\partial \theta_j} \frac{1}{2} (h_\theta(x) - y)^2 \\ &= 2 \cdot \frac{1}{2} (h_\theta(x) - y) \cdot \frac{\partial}{\partial \theta_j} (h_\theta(x) - y) \\ &= (h_\theta(x) - y) \cdot \frac{\partial}{\partial \theta_j} \left(\sum_{i=0}^n \theta_i x_i - y \right) \\ &= (h_\theta(x) - y) x_j\end{aligned}$$

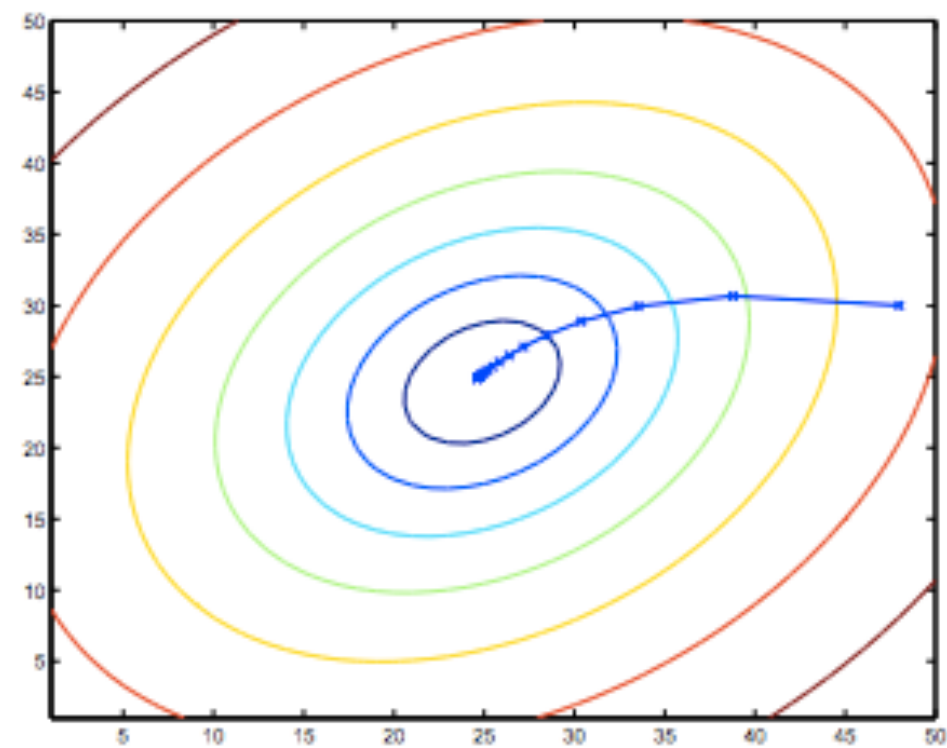
Update Rule: $\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta).$

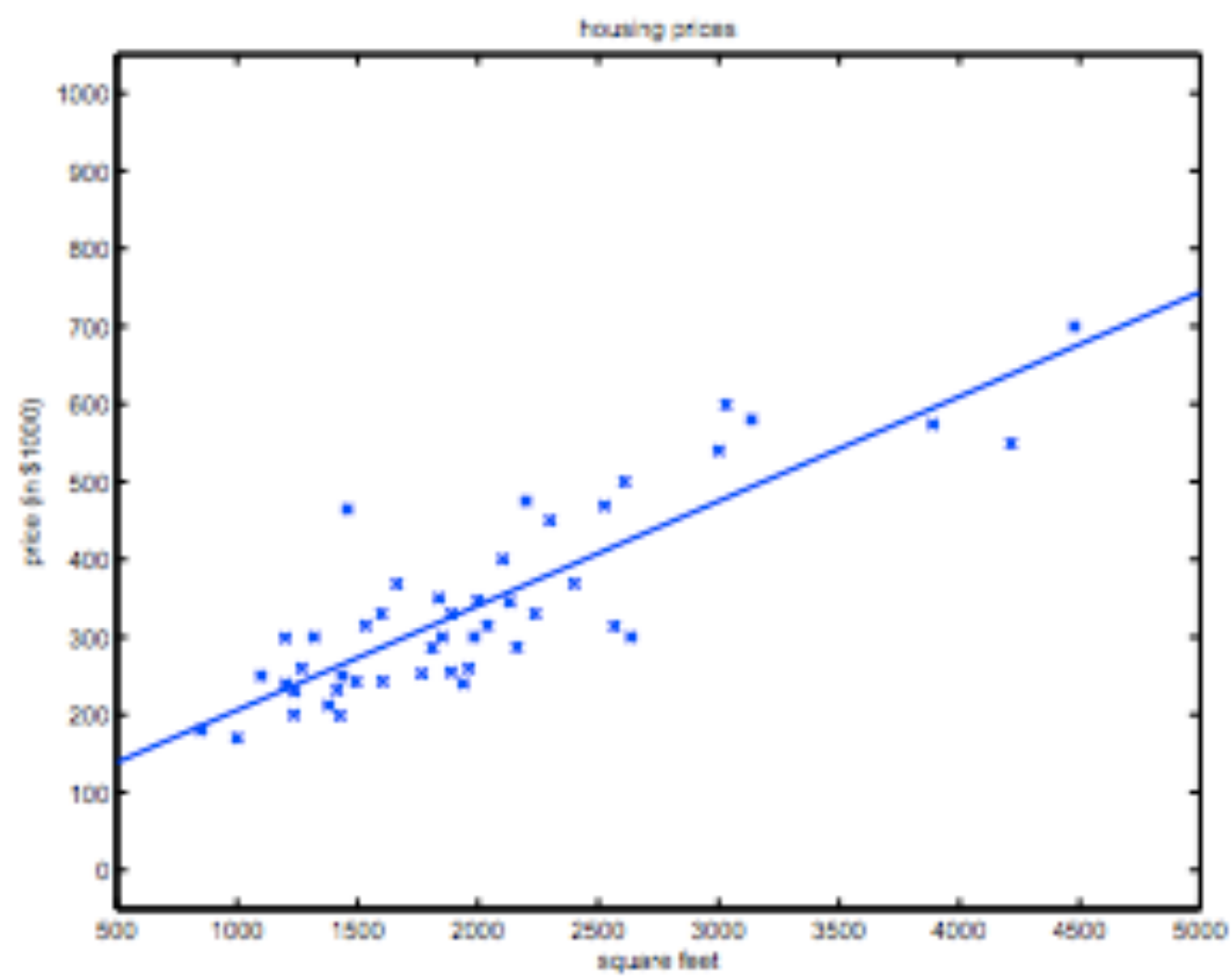
Repeat until convergence {

$$\theta_j := \theta_j + \alpha \sum_{i=1}^m (y^{(i)} - h_\theta(x^{(i)})) x_j^{(i)} \quad (\text{for every } j).$$

}

What are the axes?





Batch vs Stochastic Descent

```
for theta:  
  for each example:  
    ...
```

```
for each example:  
  for theta:  
    ...
```

Normal Equations

Don't worry!

$$\begin{aligned}\nabla_{\theta} J(\theta) &= \nabla_{\theta} \frac{1}{2} (X\theta - \vec{y})^T (X\theta - \vec{y}) \\ &= \frac{1}{2} \nabla_{\theta} (\theta^T X^T X \theta - \theta^T X^T \vec{y} - \vec{y}^T X \theta + \vec{y}^T \vec{y}) \\ &= \frac{1}{2} \nabla_{\theta} \text{tr} (\theta^T X^T X \theta - \theta^T X^T \vec{y} - \vec{y}^T X \theta + \vec{y}^T \vec{y}) \\ &= \frac{1}{2} \nabla_{\theta} (\text{tr} \theta^T X^T X \theta - 2 \text{tr} \vec{y}^T X \theta) \\ &= \frac{1}{2} (X^T X \theta + X^T X \theta - 2 X^T \vec{y}) \\ &= X^T X \theta - X^T \vec{y}\end{aligned}$$

Worry.

$$\theta = (X^T X)^{-1} X^T \vec{y}.$$

Probabilistic Interpretation

$$y^{(i)} = \theta^T x^{(i)} + \epsilon^{(i)}$$

$$p(\epsilon^{(i)}) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(\epsilon^{(i)})^2}{2\sigma^2}\right).$$

We can minimise **cost**
or
maximise likelihood

What's the likelihood?

Likelihood

$$\begin{aligned} L(\theta) &= \prod_{i=1}^m p(y^{(i)} \mid x^{(i)}; \theta) \\ &= \prod_{i=1}^m \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(y^{(i)} - \theta^T x^{(i)})^2}{2\sigma^2}\right) \end{aligned}$$

Can you write this as a sum?

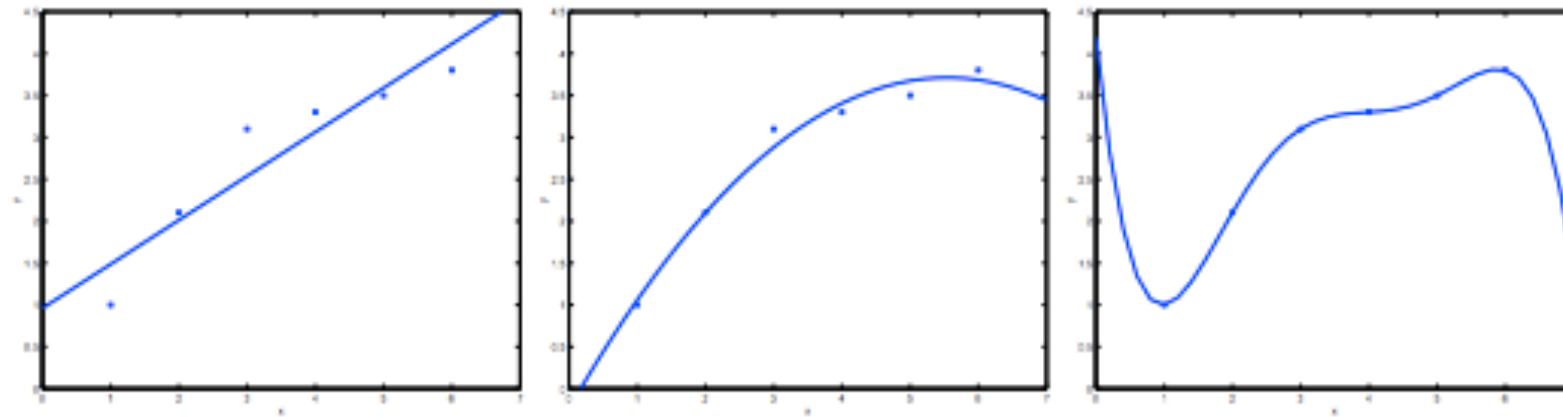
Likelihood - For you advanced folks

$$\begin{aligned}\ell(\theta) &= \log L(\theta) \\ &= \log \prod_{i=1}^m \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(y^{(i)} - \theta^T x^{(i)})^2}{2\sigma^2}\right) \\ &= \sum_{i=1}^m \log \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(y^{(i)} - \theta^T x^{(i)})^2}{2\sigma^2}\right) \\ &= m \log \frac{1}{\sqrt{2\pi}\sigma} - \frac{1}{\sigma^2} \cdot \frac{1}{2} \sum_{i=1}^m (y^{(i)} - \theta^T x^{(i)})^2.\end{aligned}$$

Hence, maximizing $\ell(\theta)$ gives the same answer as minimizing

$$\frac{1}{2} \sum_{i=1}^m (y^{(i)} - \theta^T x^{(i)})^2,$$

Locally Weighted Linear Regression



classic tradeoff

Locally Weighted Linear Regression

Instead of doing

1. Fit θ to minimize $\sum_i (y^{(i)} - \theta^T x^{(i)})^2$.
2. Output $\theta^T x$.

we do

1. Fit θ to minimize $\sum_i w^{(i)} (y^{(i)} - \theta^T x^{(i)})^2$.
2. Output $\theta^T x$.

Locally Weighted Linear Regression

Good examples of weights?

Locally Weighted Linear Regression

Good examples of weights?

$$w^{(i)} = \exp\left(-\frac{(x^{(i)} - x)^2}{2\tau^2}\right)$$

Locally Weighted Linear Regression

Parametric vs Non-Parametric

What was k-Nearest Neighbours?