





Regression

With Linear Regression MODALG SoSe18







News & Motivation

META MARATHON Artificial intelligenc

42 radical-explorative hours NRW-Forum Düsseldorf May 25 — 27, 2018







42 Stunden nonstop Talks, Performances, Filme, Konzerte, Ausstellung und Workshops zum Thema Künstliche Intelligenz: Der META Marathon ist ein neuartiges Technologie-Festival, das vom 25. bis 27. Mai 2018 im NRW-Forum Düsseldorf stattfindet. Die Teilnehmer gestalten das Festival selbst, wechseln die Rollen vom Experten zum Laien und experimentieren mit dem neuen Format – inklusive Übernachtung vor Ort. Festivaldirektor ist der Futurist und Unternehmer Christopher Peterka.







Advantages:

- Participants who can show a three day participation receive three points for this class
- Three days for free do it!!!
- Networking and learn cool Al-Stuff
- Our Workshop: Reinforcement-Learning with DQN's
- Timeslot: Sa. 26.5., 11 am. to 15 pm.

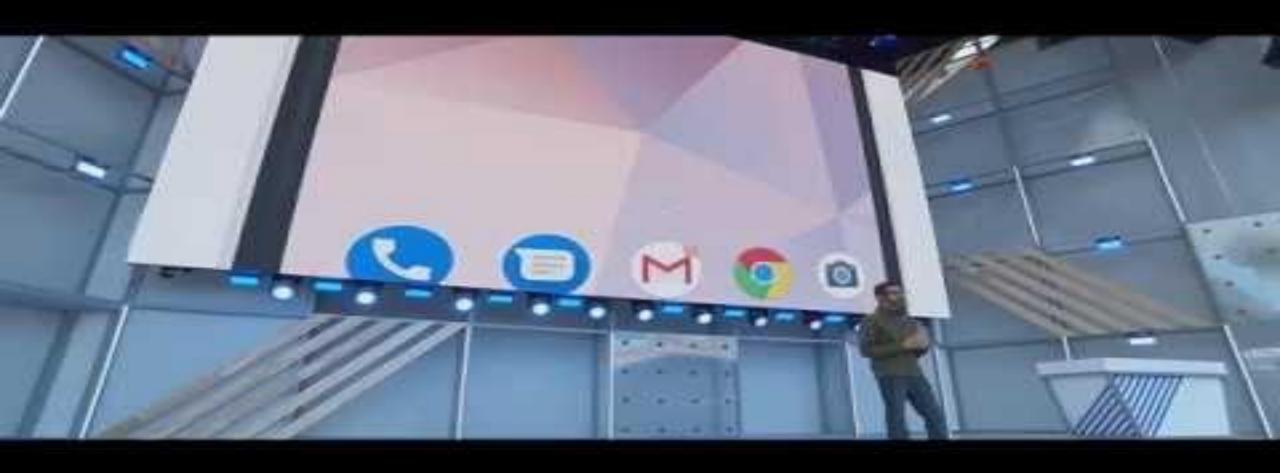






Important:

- Send me your confirmation and your name till 16.05.18, 18 pm.
- marcel.tiator@study.hs-duesseldorf.de
- Use subject: "META Marathon"
- More Information: https://www.nrwforum.de/veranstaltungen/meta-marathon



```
stre.flame[get]script site
  (245, 23,068,789,a48) [b
  // script src= address [#b da ]
  status.command
 pinput.[true]
   ("true") add.string ( status) (
input.false function
         eccint scc=[true]
```













Topics:

- Supervised Learning & Classification
- Regression
- Linear Regression
- Gradient Descent
- Introduction Tensorflow
- Programming Exercise







Machine Learning

Supervised Learning

Reinforcement Learning Unsupervised Learning

Classification

Regression

Clustering







$$y = f(x)$$

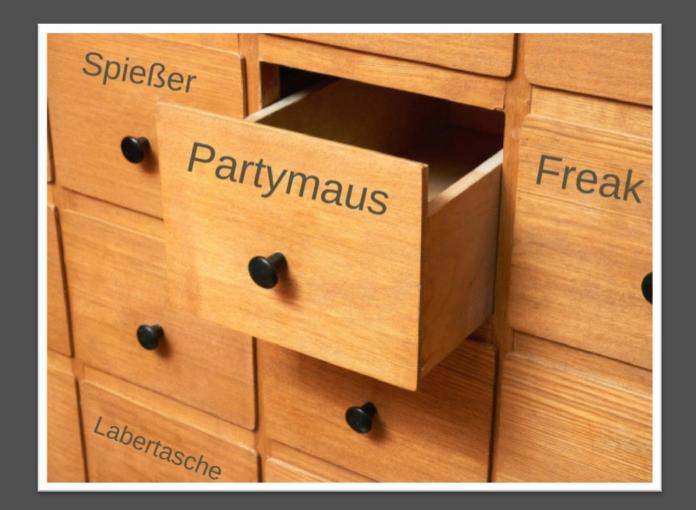






What is the aim of classification?

- Differentiation
- $y \in \{Partymaus, \\ Spie Ser, \\ Freak\}$





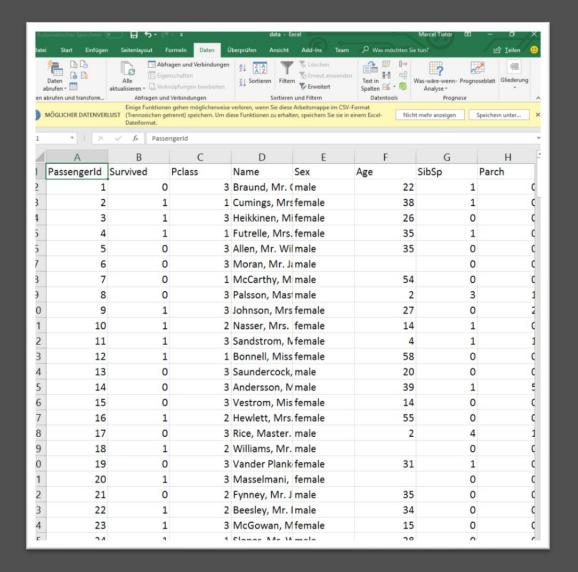




Tabular Data

y: Survived $y \in \{0,1\}$









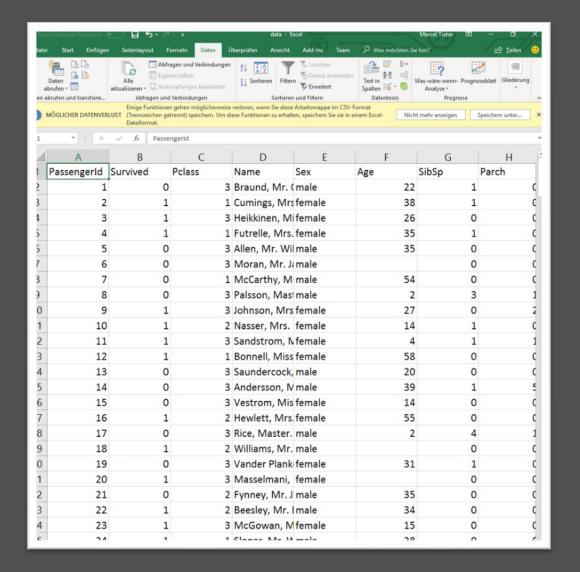


Tabular Data

x: class, sex, age

e.g. $x = (1,1,45)^T$











Discrete vs. Continuous

$$y \in N^n$$

Example:

$$y \in \{0,1,2,3,4\}$$

 $y \in \{(1,0,0),$
 $(0,1,0),$
 $(0,0,1)\}$

$$y \in R^n$$

Example:

$$y \in \{0.1, -0.43, 3.44\}$$

 $y \in \{(-0.2, 0.3, -0.7),$
 $(3.1, 5.0, -0.62),$
 $(0.44, -0.4, 4.5)\}$







Regression







y: DAX

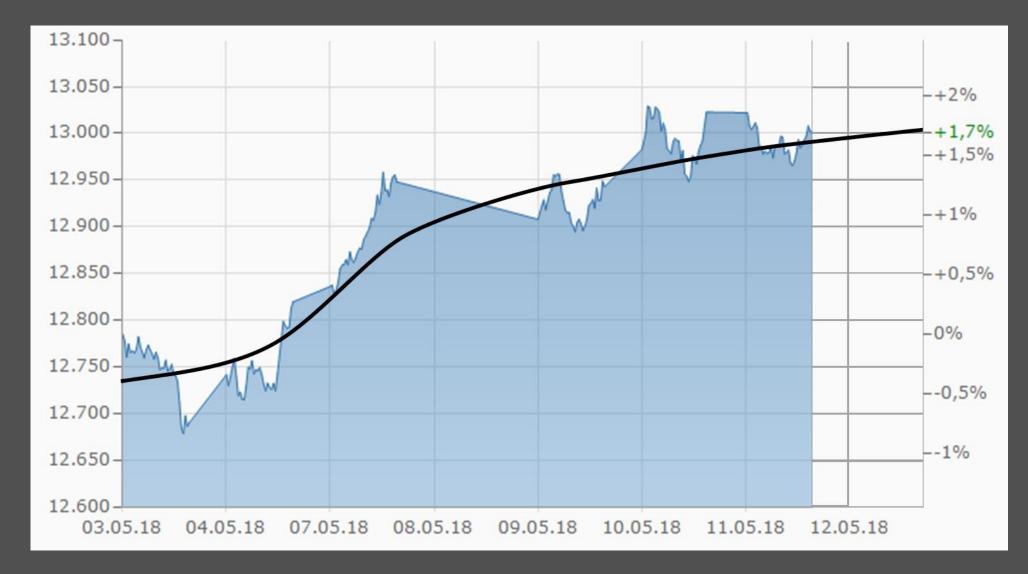








y: DAX









x: Dow Jones









Date	x: Dow Jones	y: DAX
08.05.18	24,300	12,940
09.05.18	24,400	12,910
10.05.18	24,600	12,975
11.05.18	24,800	13,020
12.05.18	24,600	???

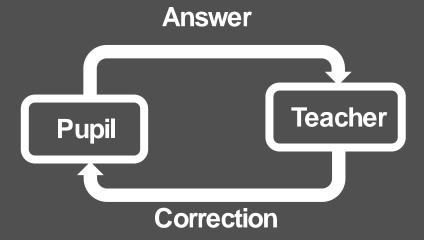


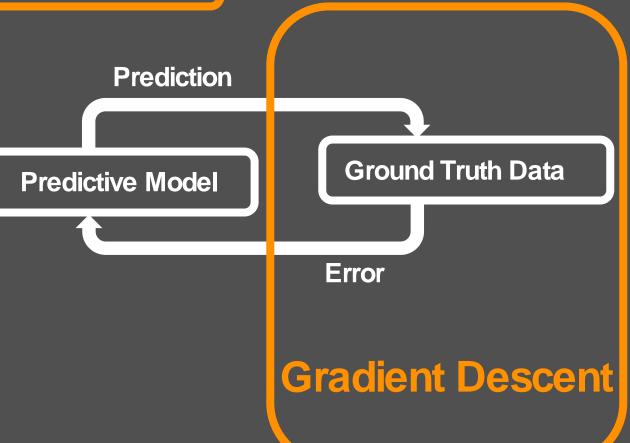




Today:

Linear Regression











Linear Regression

Predictive Model:

- $\bullet \quad \hat{y} = \theta_1 x_1 + \theta_0 x_0$
- Weights: $\theta_0, \theta_1 \in R$
- $x_0 = 1$

Predictive Model:

- $\hat{y} = mx + b$
- $m = \theta_1$
- $x = x_1$
- $b = \theta_0 x_0$



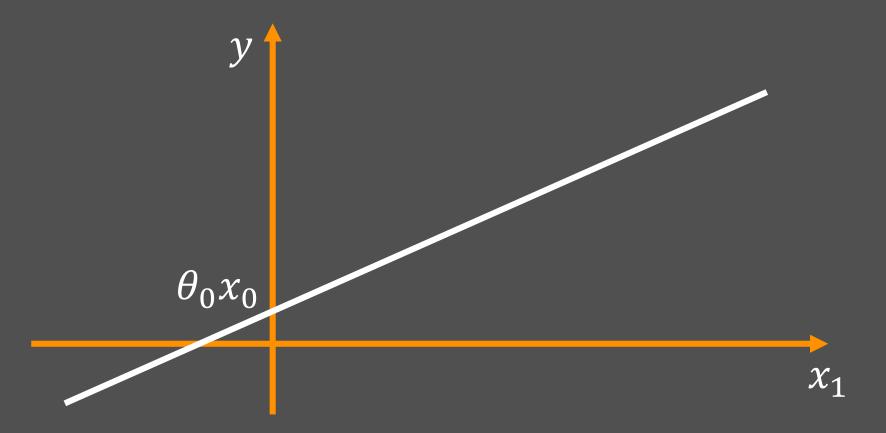




Linear Regression

Slope of the line depends on weights θ_0 , θ_1



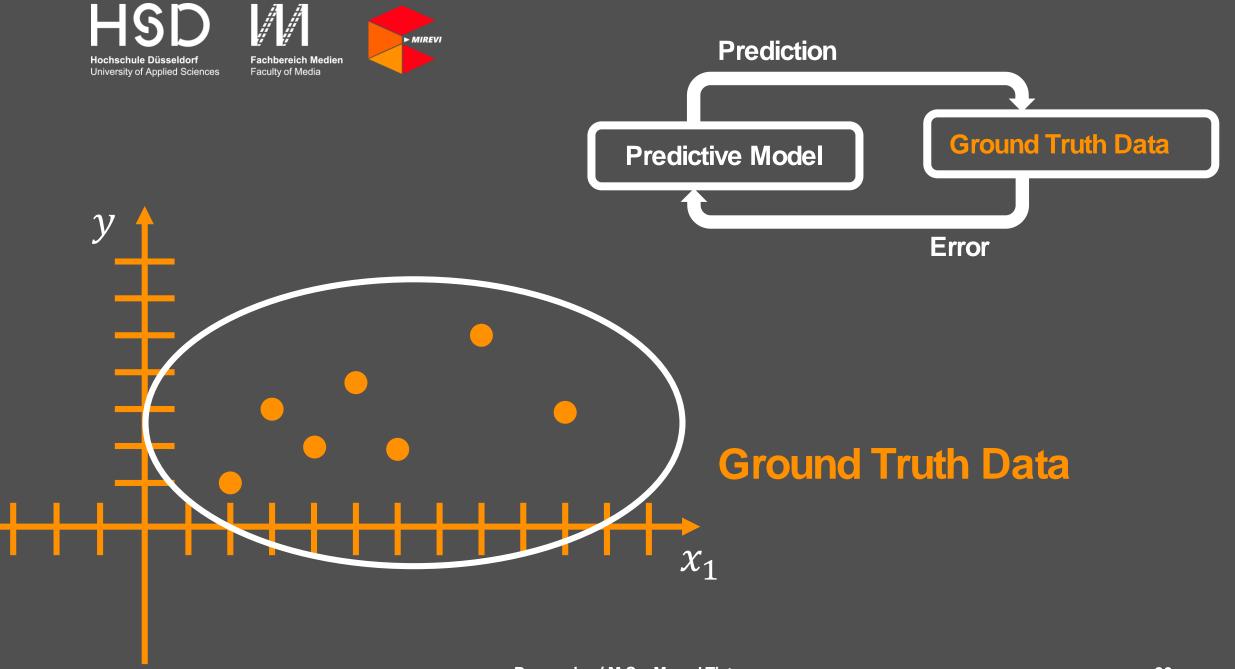








Find good weights!



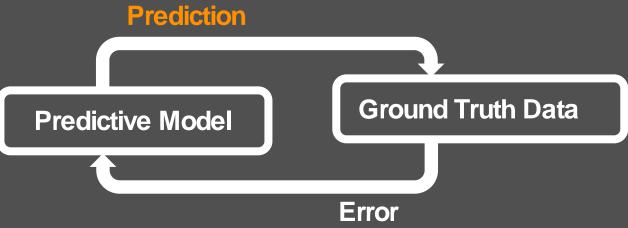


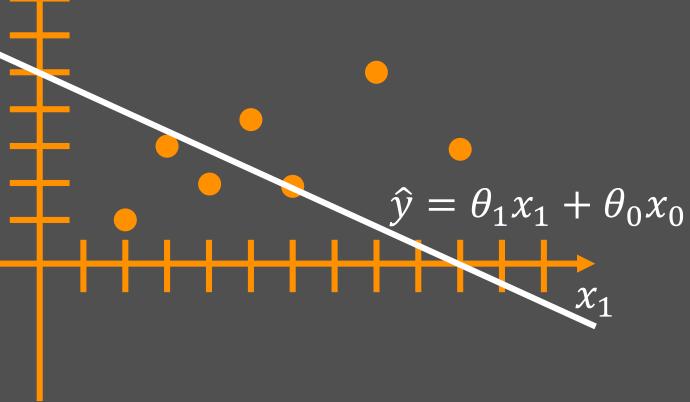




Random Weights

















Ground Truth Data



$$E = \frac{1}{2m} \sum_{i=1}^{m} (\hat{y}_i - y_i)^2$$











Ground Truth Data

Error

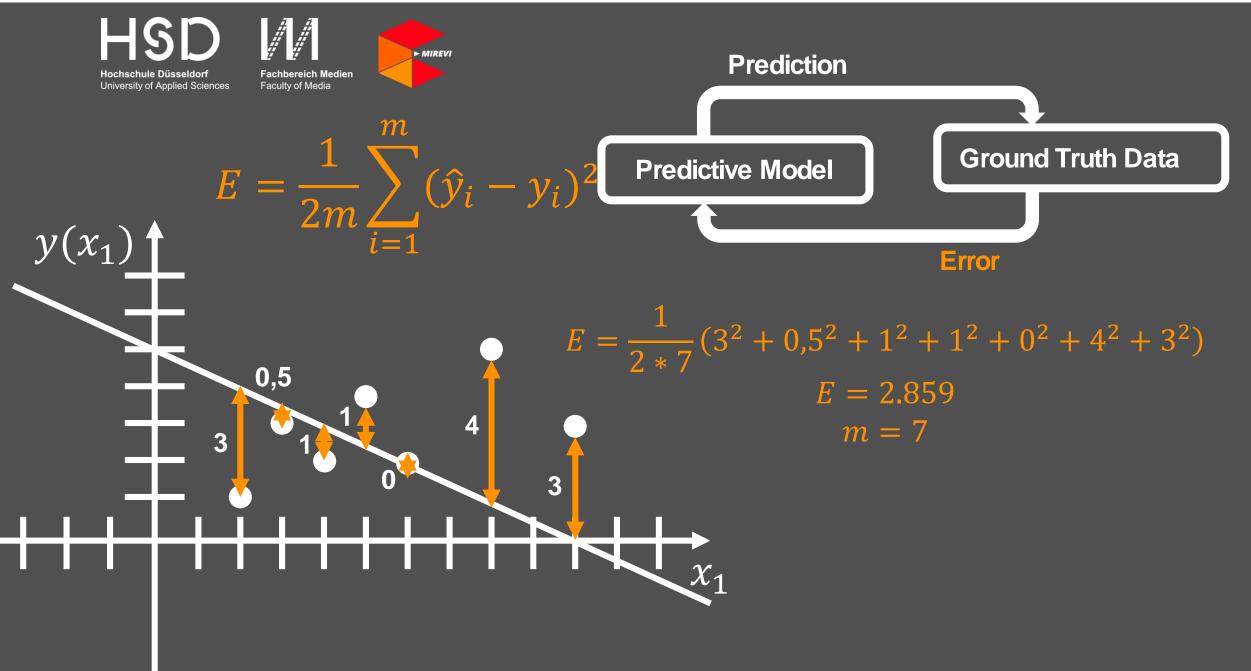
$$y(x_1)$$

$$0.5$$

$$E =$$

$$x_1$$

$$E = \frac{1}{2m} \sum_{i=1}^{m} (\hat{y}_i - y_i)^2$$









Prediction would be as good as error of 2,589







Gradient Descent:

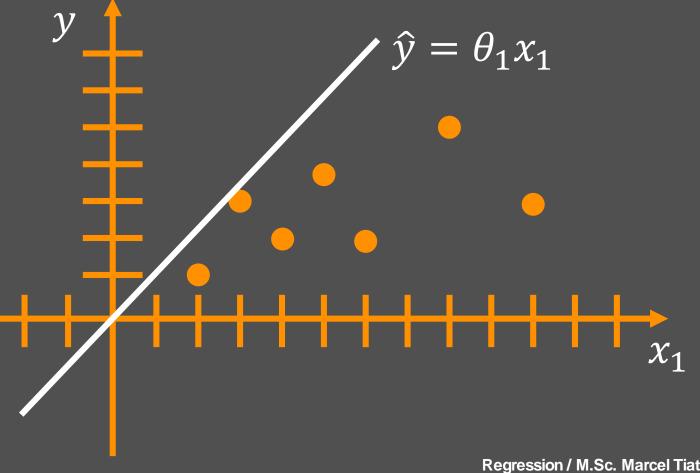
- Tune weigths: θ_0 , θ_1
- Minimize error
- Formally: $\min_{\theta_0,\theta_1} E(\overline{\theta_0},\overline{\theta_1})$
- Prediction fits better to data
- Training Process







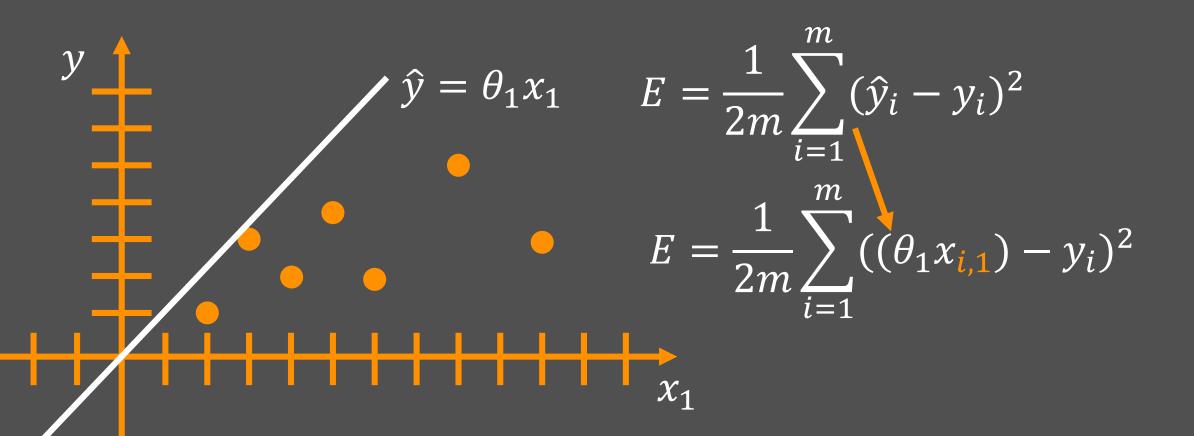
Let's facilitate the problem for visualization

















$$E = \frac{1}{2m} \sum_{i=1}^{m} (\hat{y}_i - y_i)^2 = \frac{1}{2m} \sum_{i=1}^{m} ((\theta_1 x_{i,1}) - y_i)^2$$

Want: $\min_{\theta_1} E(\theta_1)$

Calculate:
$$\frac{\partial E(\theta_1)}{\partial \theta_1} = 2 * \frac{1}{2m} * \sum_{i=1}^{m} ((\theta_1 x_{i,1}) - y_i) * x_{i,1}$$

$$\frac{\partial E(\theta_1)}{\partial \theta_1} = \frac{1}{m} \sum_{i=1}^m \left(\left(\theta_1 x_{i,1} \right) - y_i \right) * x_{i,1}$$







Tune weight: θ_1

$$\theta_1 \coloneqq \theta_1 - \alpha * \frac{\partial E(\theta_1)}{\partial \theta_1}$$

Algorithm:

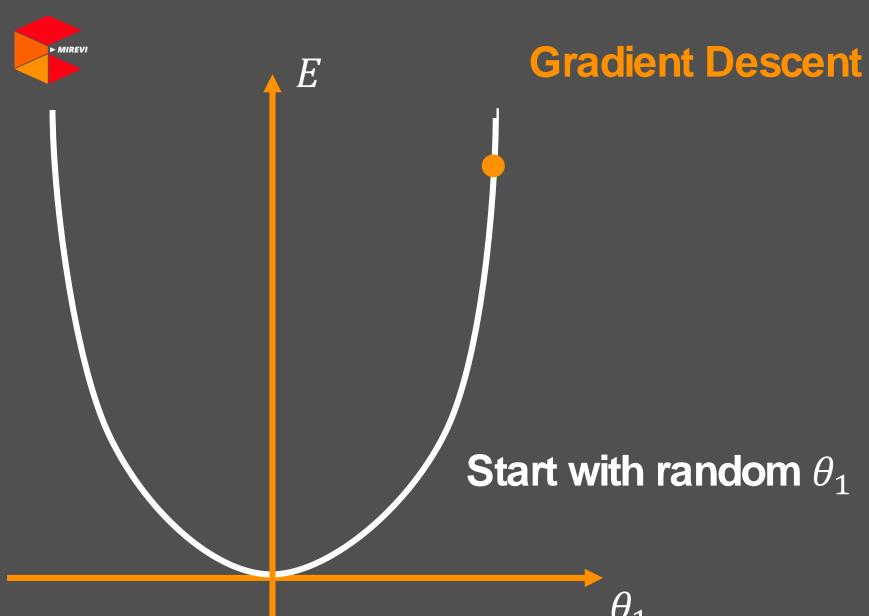
Start with random θ_1 repeat until convergence{

$$\theta_1 \coloneqq \theta_1 - \alpha * \frac{\partial E(\theta_1)}{\partial \theta_1}$$

}













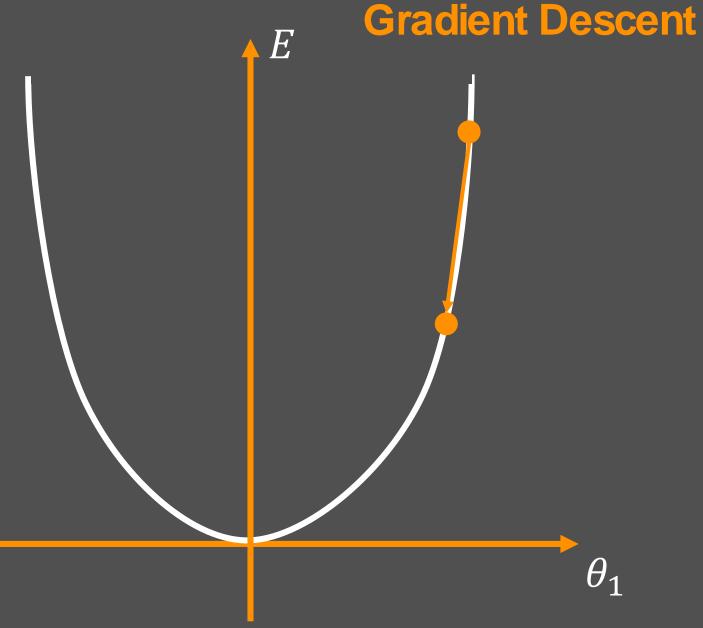
► MIREVI

repeat until convergence{

$$\theta_1 \coloneqq \theta_1 - \alpha * \frac{\partial E(\theta_1)}{\partial \theta_1}$$

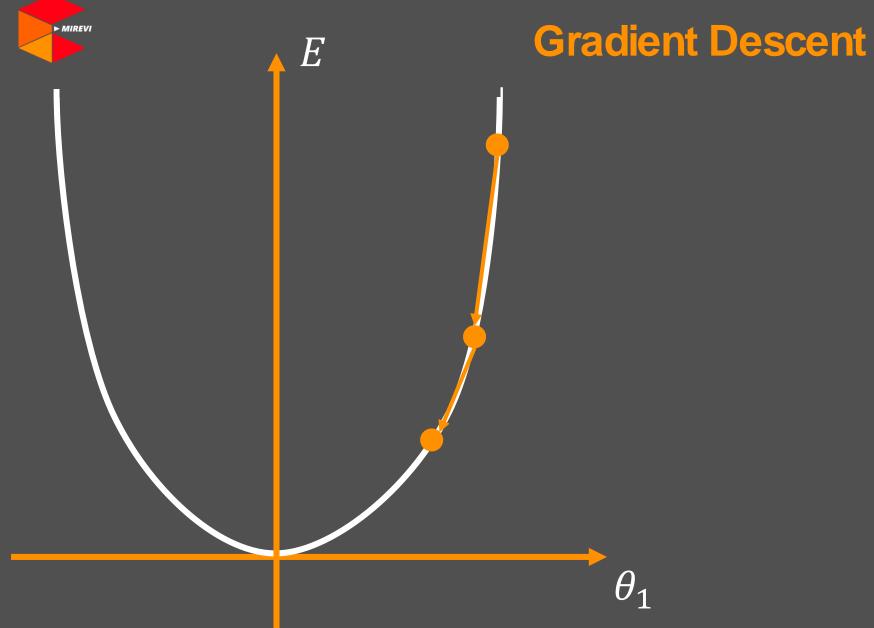
 α : Learning Rate

$$\alpha = const.$$





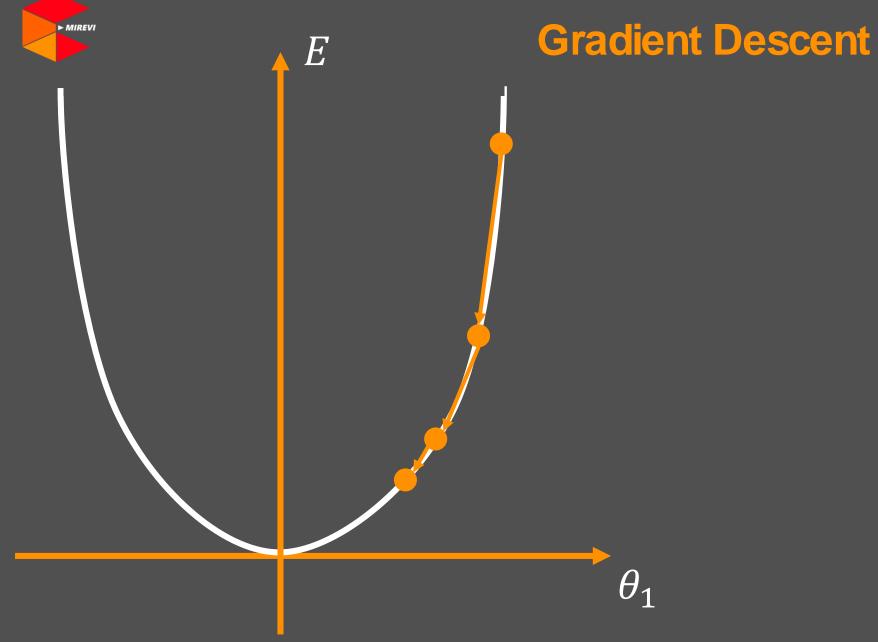












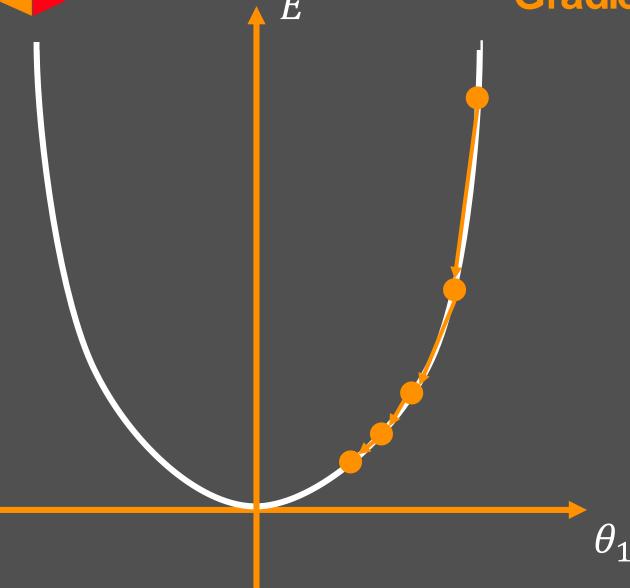






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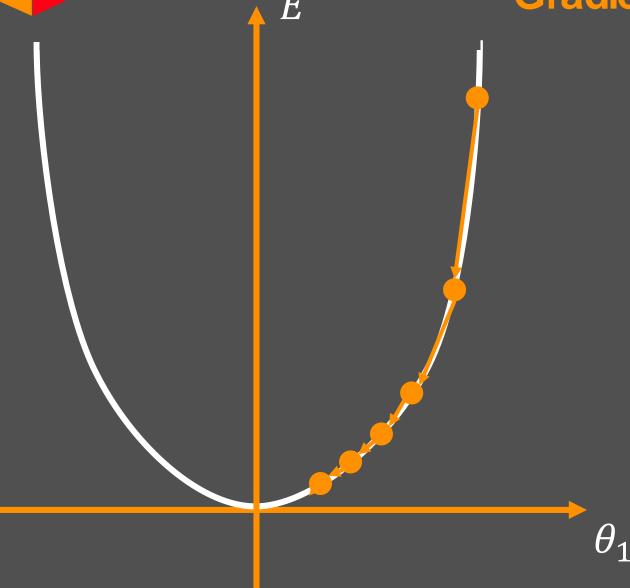


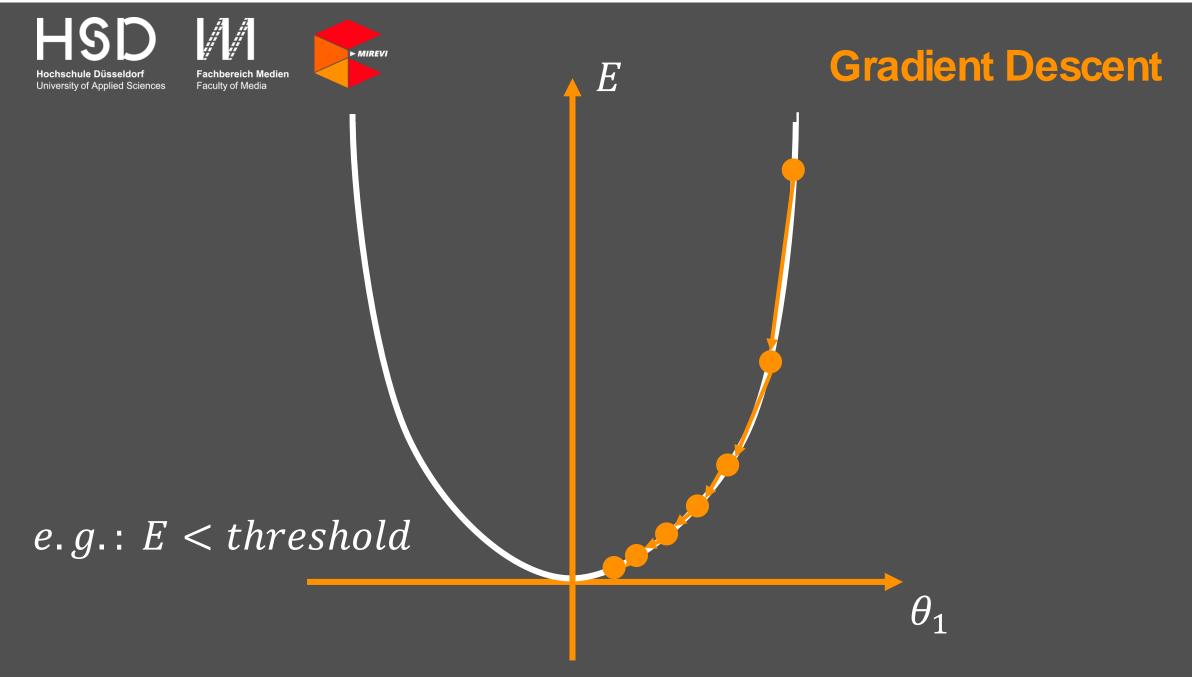




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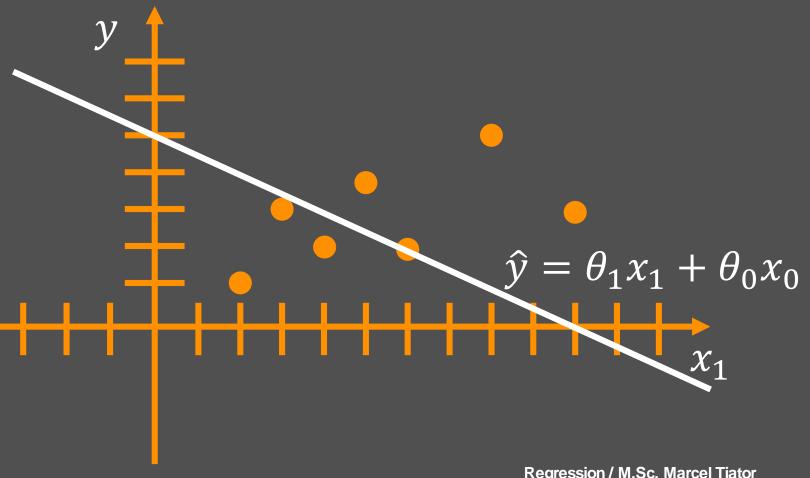








Two weights:









$$E = \frac{1}{2m} \sum_{i=1}^{m} (\hat{y}_i - y_i)^2 = \frac{1}{2m} \sum_{i=1}^{m} ((\theta_1 x_{i,1} + \theta_0 x_{i,0}) - y_i)^2$$

Want: $\min_{\theta_0, \theta_1} E(\theta_0, \theta_1)$

$$\frac{\partial E(\boldsymbol{\theta_0}, \boldsymbol{\theta_1})}{\partial \boldsymbol{\theta_1}} = \frac{1}{m} \sum_{i=1}^{m} \left(\left(\boldsymbol{\theta_1} \boldsymbol{x_{i,1}} \right) - \boldsymbol{y_i} \right) * \boldsymbol{x_{i,1}}$$

$$\frac{\partial E(\boldsymbol{\theta_0}, \boldsymbol{\theta_1})}{\partial \boldsymbol{\theta_0}} = \frac{1}{m} \sum_{i=1}^{m} \left(\left(\boldsymbol{\theta_0} \boldsymbol{x_{i,0}} \right) - \boldsymbol{y_i} \right) * \boldsymbol{x_{i,0}}$$

$$= \frac{1}{m} \sum_{i=1}^{m} \left(\left(\boldsymbol{\theta_0} \boldsymbol{x_{i,0}} \right) - \boldsymbol{y_i} \right), \boldsymbol{x_{i,0}} = 1$$







Start with random θ_0 , θ_1 repeat until convergence{

$$\theta_0 \coloneqq \theta_0 - \alpha * \frac{\partial E(\theta_0, \theta_1)}{\partial \theta_0}$$

$$\theta_1 \coloneqq \theta_1 - \alpha * \frac{\partial E(\theta_0, \theta_1)}{\partial \theta_1}$$







Implementation note:

Start with random θ_0 , θ_1 repeat until convergence{

$$tmp_0 \coloneqq \theta_0 - \alpha * \frac{\partial E(\theta_0, \theta_1)}{\partial \theta_0}$$

$$tmp_1 \coloneqq \theta_1 - \alpha * \frac{\partial E(\theta_0, \theta_1)}{\partial \theta_1}$$

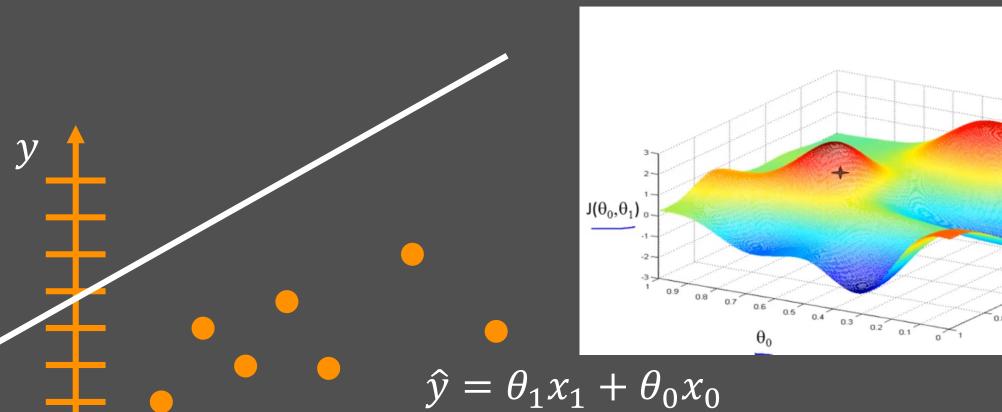
$$\theta_0 \coloneqq tmp_0$$

$$\theta_1 \coloneqq tmp_1$$





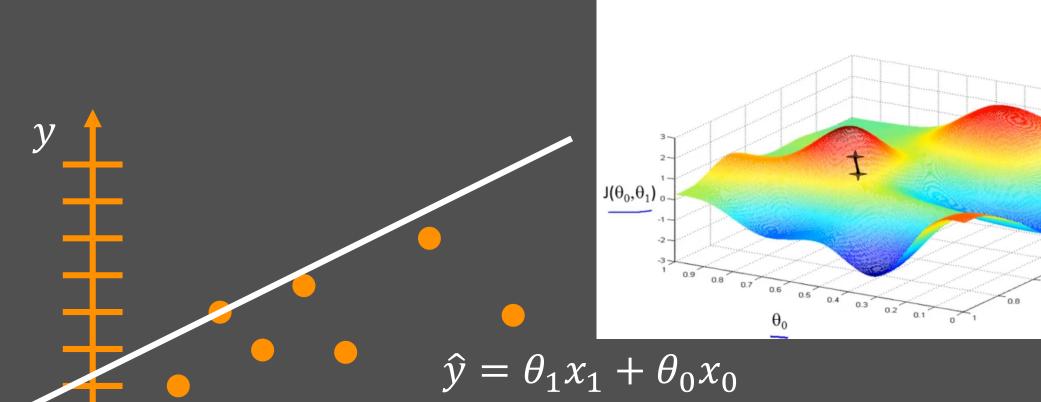








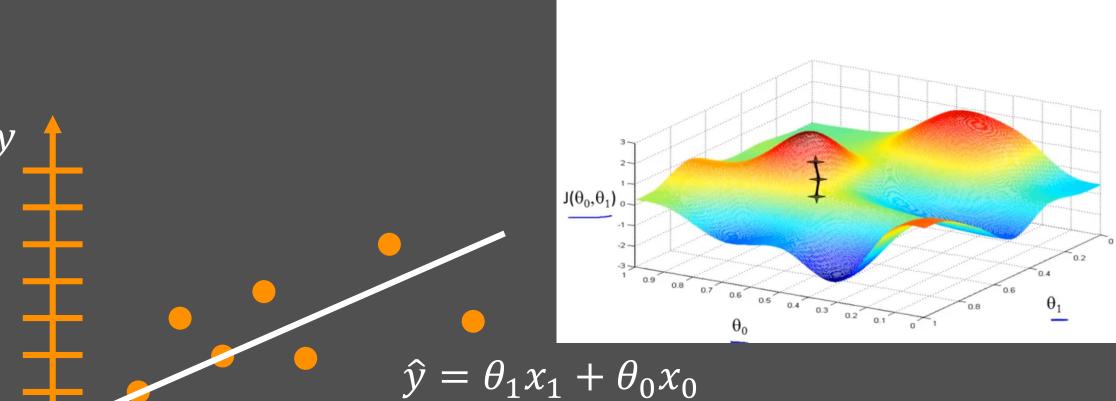












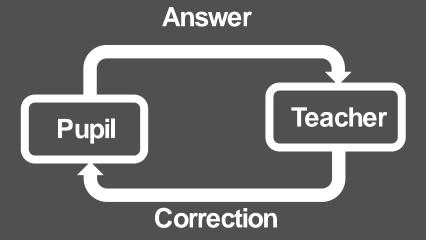


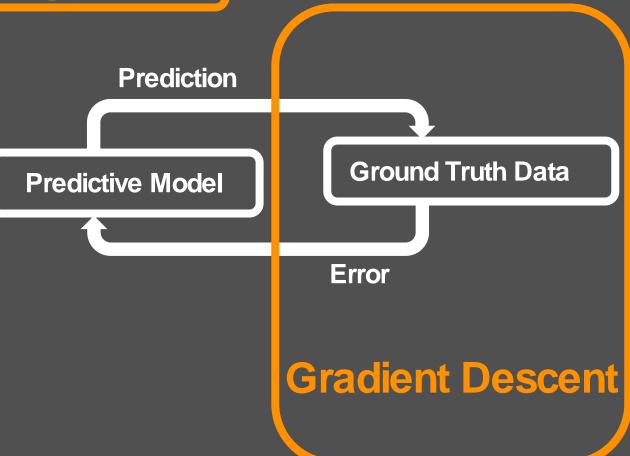




You learned:

Linear Regression









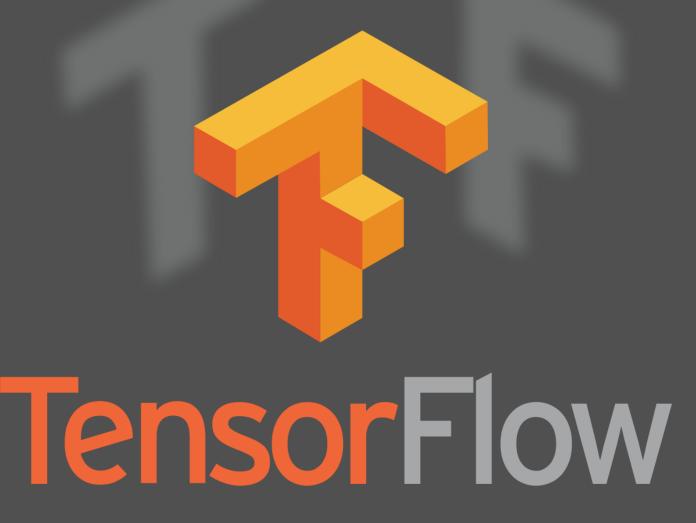


Questions?















About:

- open source software library for high performance numerical computation
- variety of platforms (CPUs, GPUs, TPUs), and from desktops to clusters of servers to mobile and edge devices
- used across many other scientific domains















































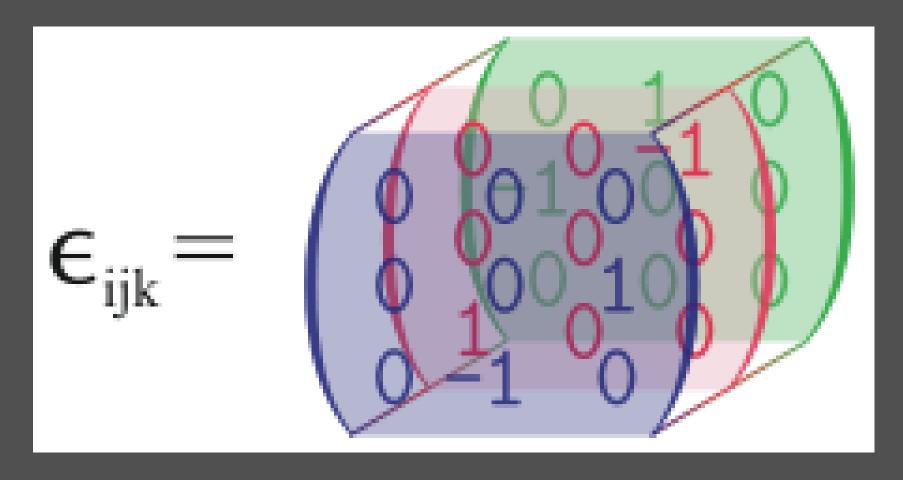








What is a Tensor? (compare with array of array of array ...)



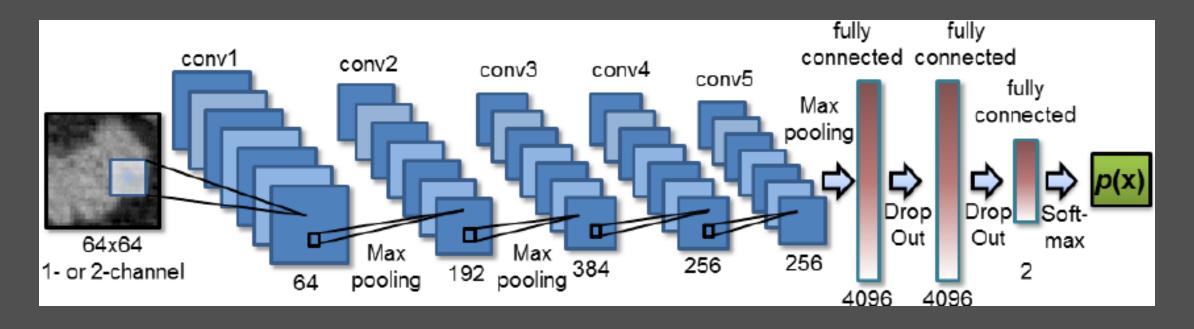






Why is this useful?

Try to describe multiple images in one mathematical structure









Basic elements:

- tf. Variable: remember θ
- tf.constant
- tf.placeholder: variable which can be used in a graph
- tf.flags: Global parameter, e.g. α :learning rate

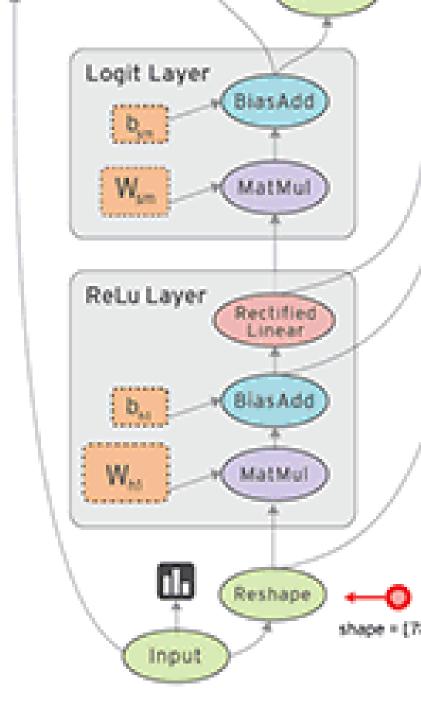






Graph:

- Blueprint of computations
- Chain of functions









tf.placeholder:

Useful for input data

tf.Variable:

Values are manipulated while training







Basic operations:

- tf.multiply(x, y): x * y element-wise
- tf.reduce_sum(x): Computes the sum of elements across dimensions of a tensor
- tf.losses.mean_squared_error(y, \hat{y}): $\frac{1}{2m}\sum_{i=1}^{m}(\hat{y}_i-y_i)^2$
- tf.add(x, y): x + y
- tf.scalar_mul(α , x): $\alpha * x$







Basic operations:

- tf.transpose(x): x^T
- tf.subtract(x, y): x y
- tf.reshape(X,shape): resizes X to new shape







Task today:

- Implement linear regression with gradient descent
- Execute "Ir_train_gd.py"
- Implement functions in "Ir_model_gd.py"
- Some helper functions "split_dataset.py"







"lr_train_gd.py":

- Load training data
- Call train function of model
- Load test data
- Test model







"lr_model_gd.py":

- inference: prediction $\hat{y} = \theta_1 x_1 + \theta_0 x_0$
- loss: computation of $E = \frac{1}{2m} \sum_{i=1}^{m} (\hat{y}_i y_i)^2$
- gradient_descent: Computation of new θ
- train: One training step







Hints:

- n: #Columns = #Features
- $\hat{y} = \theta_n x_n + \theta_{n-1} x_{n-1} + \dots + \theta_1 x_1 + \theta_0 x_0$
- $\hat{y} = \theta x$
- Use print! For instance: print shape of tensor (tf.shape)







https://github.com/mati3230/modalg181