Supervised learning

Train the learners

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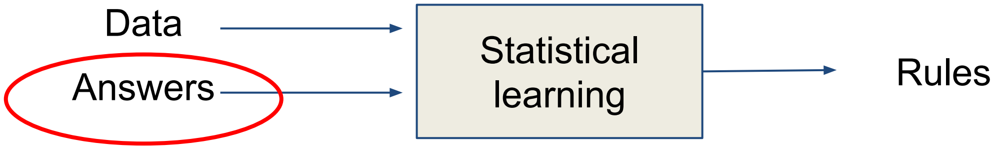
Supervised learning problems



We know the answers (and feed them to the predictive algorithm)

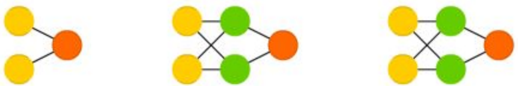
Why supervised?

Training examples

measured variables / features
on *n* examples

$$\begin{bmatrix} 1 \\ 0 \\ \vdots \\ 1 \end{bmatrix} = \begin{bmatrix} 0.12 & 1.5 & \dots & 0.9 \\ 2.05 & 0.95 & \dots & 1.1 \\ \vdots & \vdots & \ddots & \vdots \\ 3.5 & 0.88 & \dots & 1.75 \end{bmatrix}$$

labels / target variables (e.g. phenotypes) on n examples

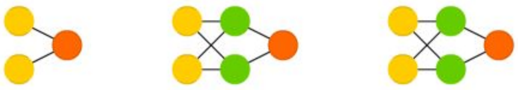


Unsupervised learning

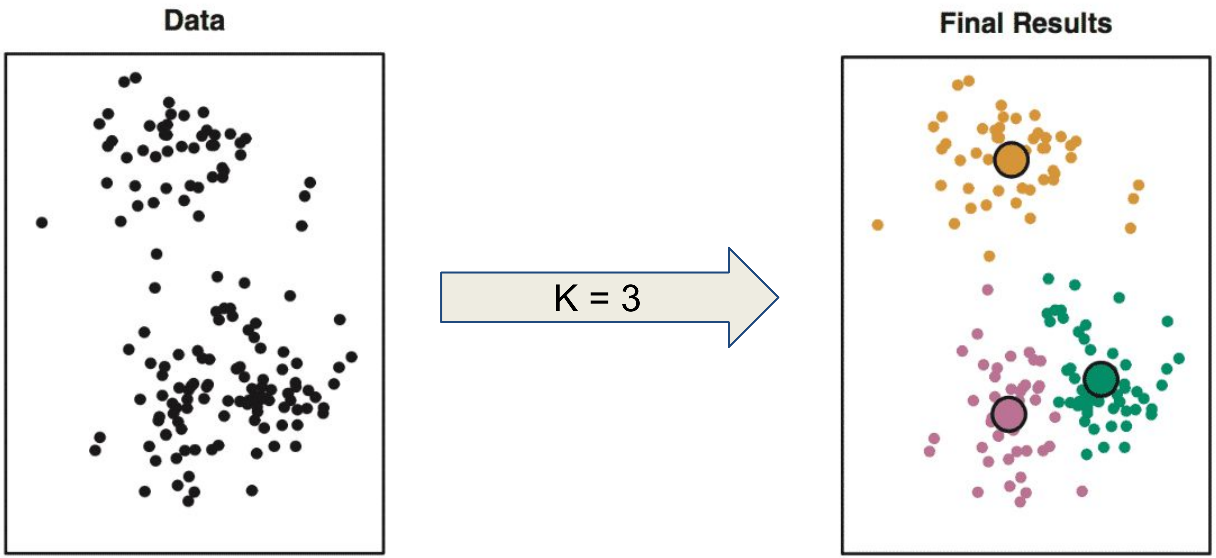
Training examples

measured variables / features
on n examples

$$\cancel{\begin{bmatrix} 1 \\ 0 \\ \vdots \\ 1 \end{bmatrix}} = \begin{bmatrix} 0.12 & 1.5 & \dots & 0.9 \\ 2.05 & 0.95 & \dots & 1.1 \\ \vdots & \vdots & \ddots & \vdots \\ 3.5 & 0.88 & \dots & 1.75 \end{bmatrix}$$



Unsupervised example: K-means clustering

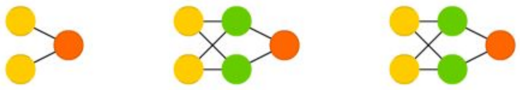


source:
https://www.iotforall.com/machine-learning-crash-course-unsupervised-learning

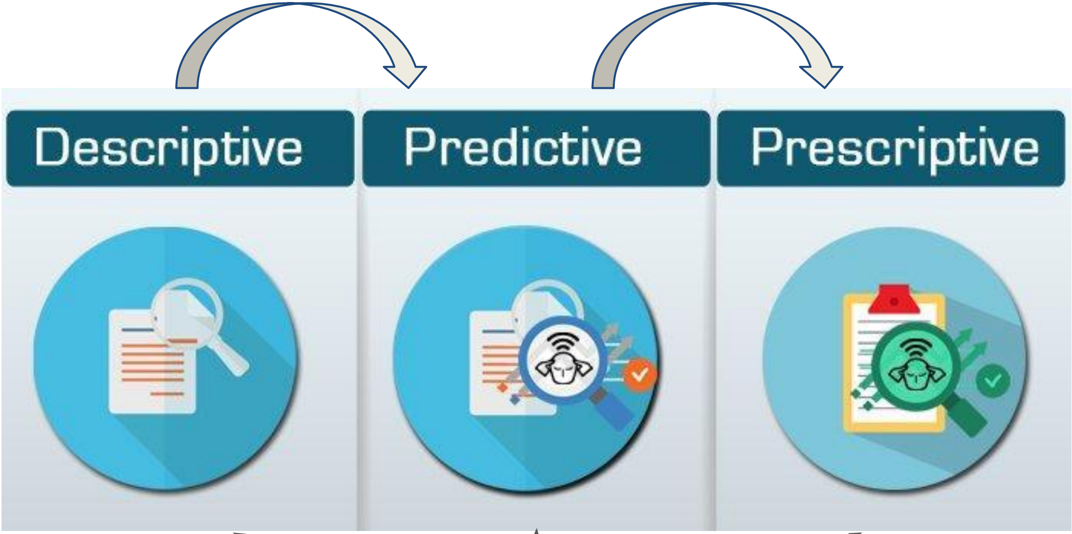
Supervised learning: Regression and classification

Supervised learning problems

- Regression (**predictive**) problems
- Classification (**predictive**) problems

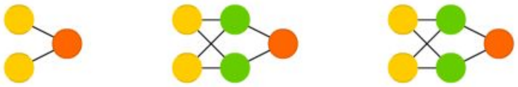


Supervised learning (predictive) problems



- Know the past
- Predict the future
- Act consequently

INFERENCE

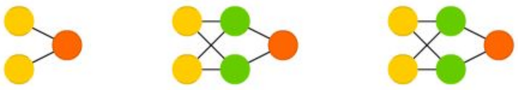


Supervised learning (predictive) problems

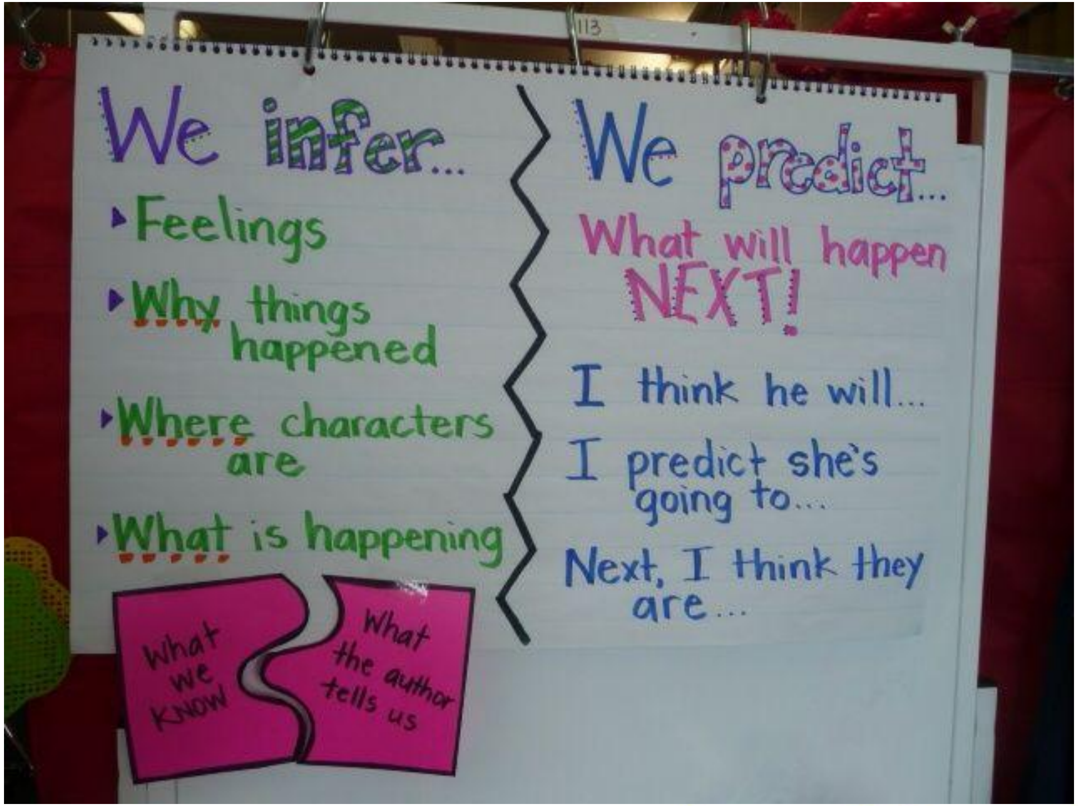
- Know the past
- Predict the future
- Act consequently

INFERENCE

- A catch-all term
- Can be confusing



Inference vs Prediction



- different statistical problems
- different objectives, different rules … different ballparks
- inference is in general more difficult than prediction

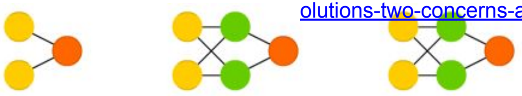
Supervised learning (predictive) problems

- Regression (**predictive**) problems
- Classification (**predictive**) problems

Predictive machines!

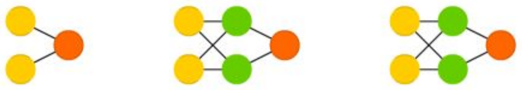
- Classifiers
- Regressors

source: https://blog.bigml.com/2013/03/12/machine-learning-from-streaming-data-two-problems-two-solutions-two-concerns-and-two-lessons/

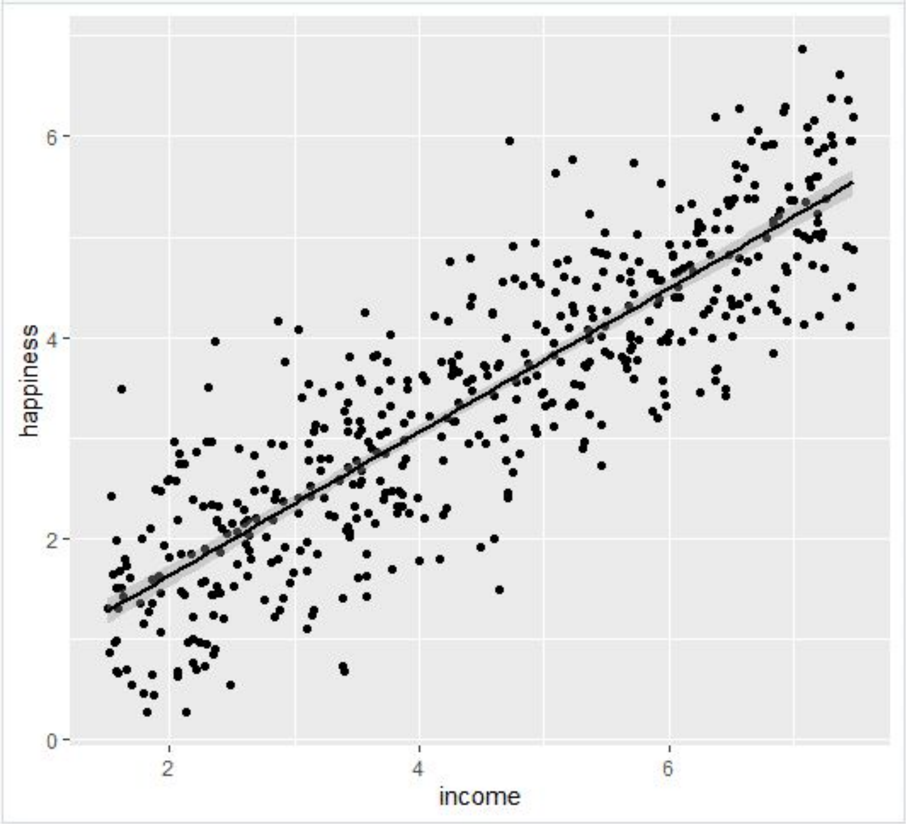


Regression problems

- the response variable **y** is **quantitative**
- e.g.: *height*, *weight*, *yield* (milk, crops), *blood sugar concentration*
- **y** = **target** (dependent) variable (a.k.a. response, objective variable)
- **X** = matrix of **features** (continuous, categorical)
- **regressor**: y = f(x) = **P(X)** ← [predictive machine]



Regression problems - simple regression



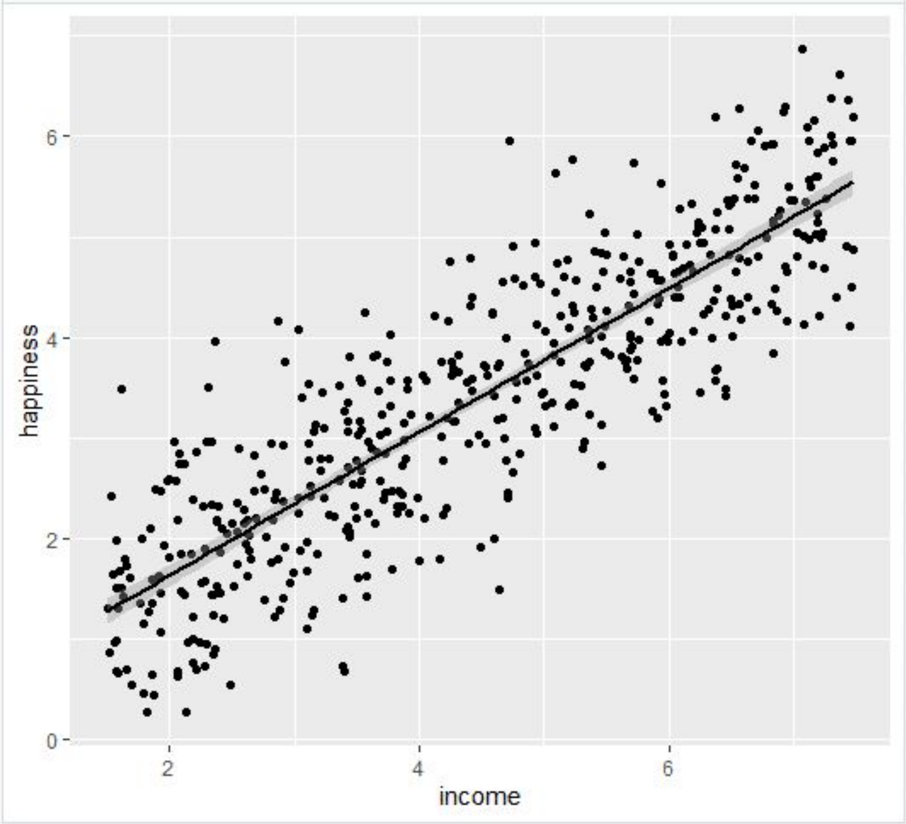
happiness = (intercept) + beta*income

or

income = (intercept) + beta*happiness

Source: https://www.scribbr.com/statistics/linear-regression-in-r/

Regression problems - simple regression



happiness = (intercept) + beta*income

or

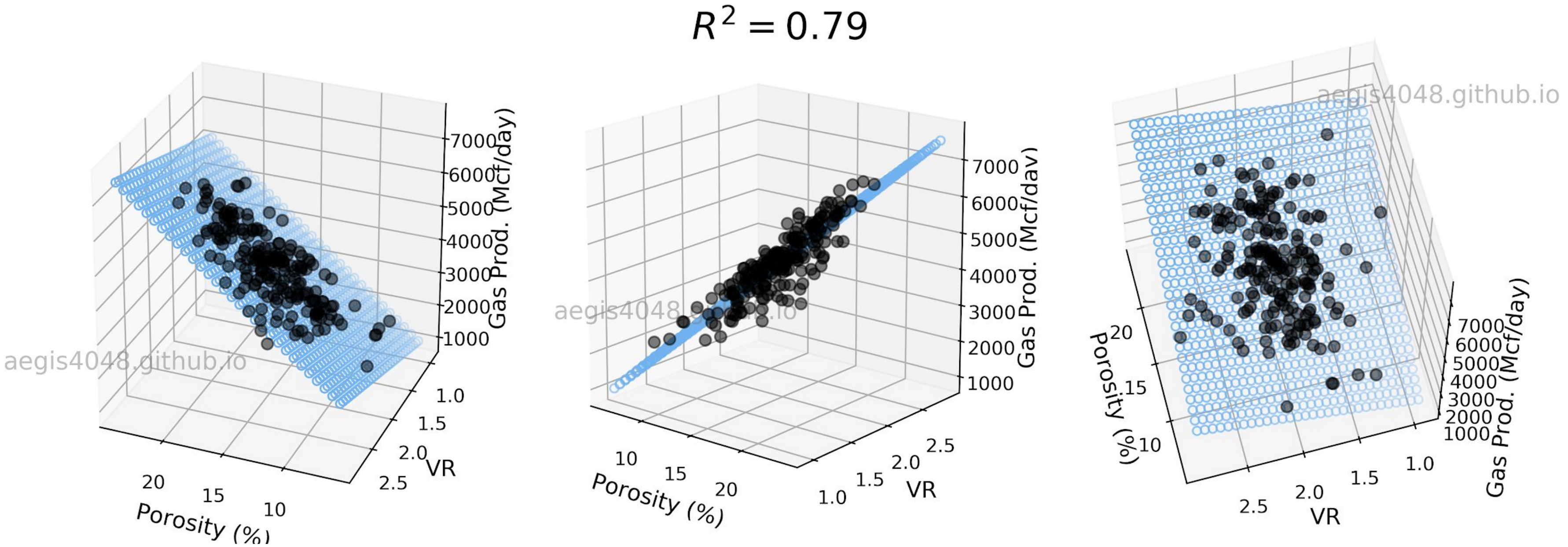
income = (intercept) + beta*happiness

cause → effect?

1. Can we predict backwards?
2. Can we make predictions if there is no cause-effect relationship?

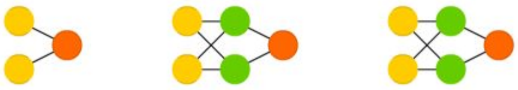
Source: https://www.scribbr.com/statistics/linear-regression-in-r/

Regression problems - multiple regression



- Gas production
- Well porosity %
- Vitrinite reflectance %

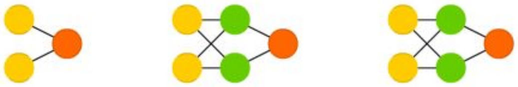
Source: https://aegis4048.github.io/mutiple_linear_regression_and_visualization_in_python



Multiple linear regression

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p + \epsilon$$

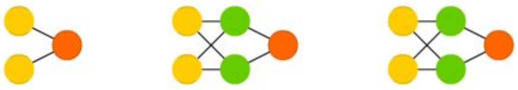
- y: target variable
- **β**’s: model coefficients
- X’s: features (predictors, independent variables, factors)



Multiple linear regression

$$\mathbf{y} = \beta\mathbf{X} + \mathbf{e}$$

- matrix (compact) notation
- vectors of observations (**y**), coefficients (**β**) and residuals (**e**)
- matrix of features (**X**)



Multiple linear regression

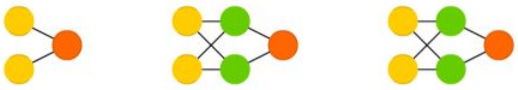
$$\mathbf{y} = \beta\mathbf{X} + \mathbf{e}$$

estimation of coefficients (learning!)

$$\hat{\mathbf{y}} = \hat{\beta}\mathbf{X}$$

→ **predictions!**

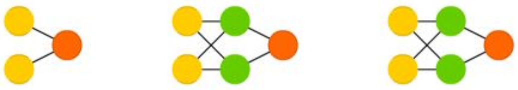
- matrix (compact) notation
- vectors of observations (**y**), coefficients (**β**) and residuals (**e**)
- matrix of features (**X**)



Predictions

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \ldots + \hat{\beta}_p x_p$$

with the estimated coefficients $\hat{\beta}$ and the feature values **X** we obtain the predicted values $\hat{y}$



Predictions

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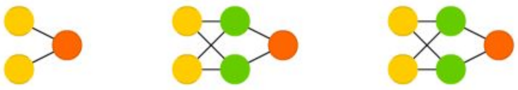
→ **how do we find the values for the the model coefficients β?**

(remember: the DL/ML models must learn the rules!)

(think about this: answer tomorrow)



Supervised learning recap

- **deep learning** is one of many methods that can be used to solve supervised learning problems
- deep learning is mainly used in **predictive problems**
- (can be used though also for inferential problems and for unsupervised learning)
- we'll see later how to use deep learning to solve linear regression