AARHUS UNIVERSITY
SCHOOL OF ENGINEERING

LESSON 4: Data analyse

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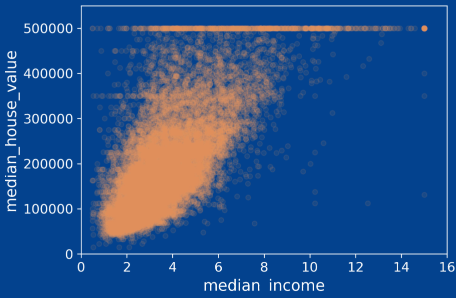
AUTUMN 2022



Agenda

Data analyse

1. Admin
   - feedback på O1 / .
2. Datasæt og Jeres O4 projekt.
   - Opgave: `L04/dataanalyse.ipynb`
3. Statestik og visualisering.
4. Pipelines
   - Opgave: `L04/pipelines.ipynb`

'Demo' datasæt

MNIST, Iris og Moon

Iris:
Sepal/petal længde/bredde,
Mr. Fisher, 1936,
"Anderson's Iris data set"
`sklearn.datasets.load_iris(..)`

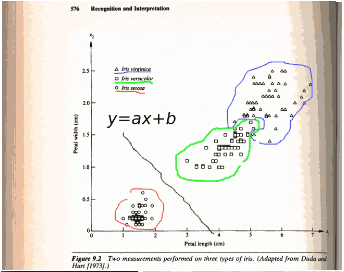
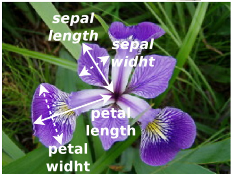
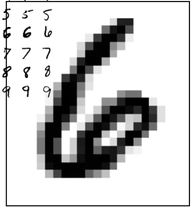


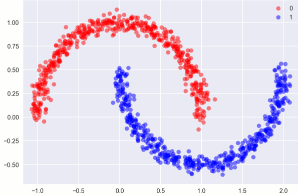
Figure 9.2 Two measurements performed on three types of iris. (Adapted from Duda and Hart [1973].)



MNIST:
Håndskrevne tal,
preprocesseret, centrerede,
`sklearn.datasets.fetch_openml('mnist_784'..`

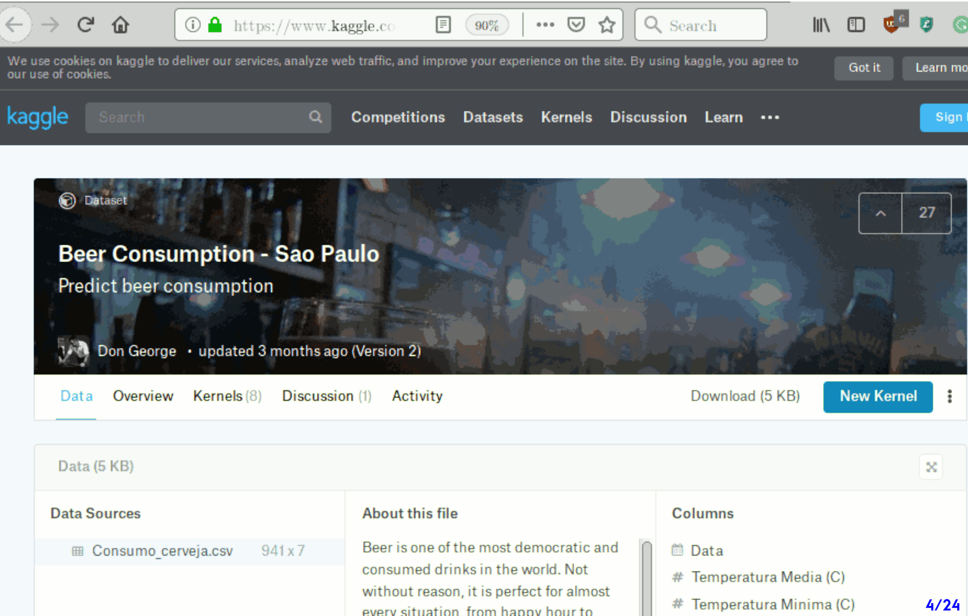


Moon:
'XOR' lign.,
non-linear decision boundary,
`sklearn.datasets.make_moons(..)`



'Dit' datasæt

Fra `https://www.kaggle.com...`



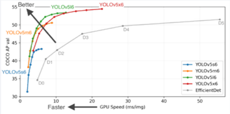
Intro til YOLOV5..

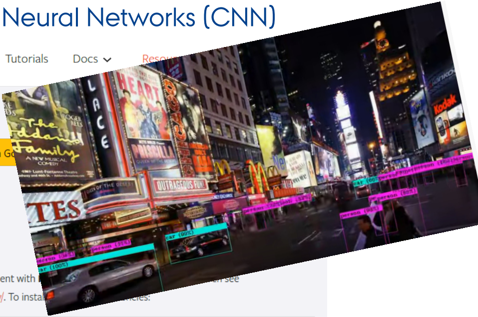
YOLOV3/4/5 Family and Convolutional Neural Networks (CNN)

PyTorch   Get Started   Ecosystem   Mobile   Blog   Tutorials   Docs

YOLOV5

View on Github   Open on G





BEFORE YOU START

Start from a **Python>=3.8** environment with

https://pytorch.org/get-started/locally/. To instal

```
pip install -qr https://raw.githubusercontent.com/ultralytics/yolov5/master/req
```

MODEL DESCRIPTION

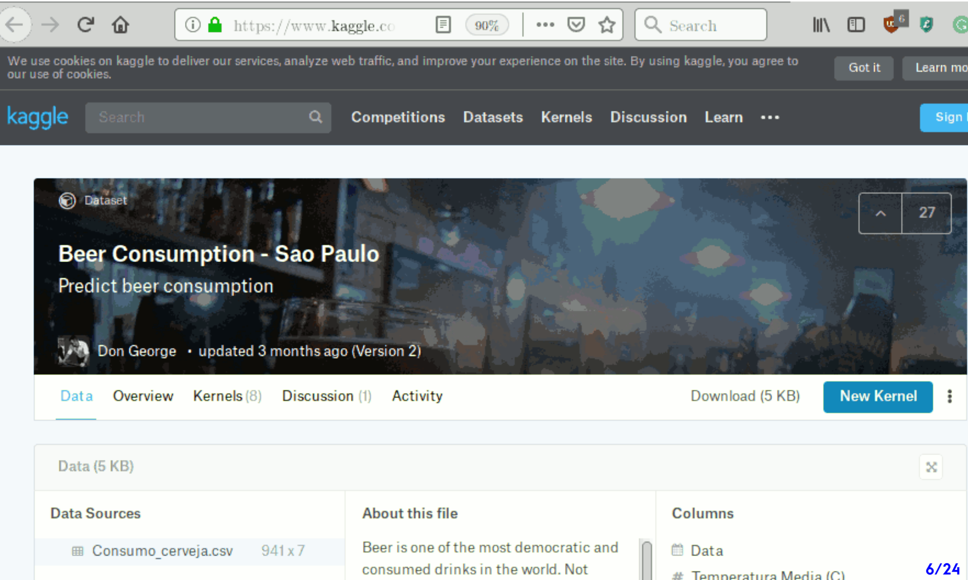
Nano	Small	Medium	Large	XLarge
YOLOv5n	YOLOv5s	YOLOv5m	YOLOv5l	YOLOv5x
4 MB_{FP16}	14 MB_{FP16}	41 MB_{FP16}	89 MB_{FP16}	166 MB_{FP16}
6.3 ms_{V100}	6.4 ms_{V100}	8.2 ms_{V100}	10.1 ms_{V100}	12.1 ms_{V100}
28.4 mAP_{COCO}	37.2 mAP_{COCO}	45.2 mAP_{COCO}	48.8 mAP_{COCO}	50.7 mAP_{COCO}

NOTE: YOLOV5 [https://pytorch.org/hub/ultralytics_yolov5/]
Demo video [https://www.youtube.com/watch?v=1_SiUOYUoOI]

Opg. L04 Beskrivelse af eget slutprojekt.pdf

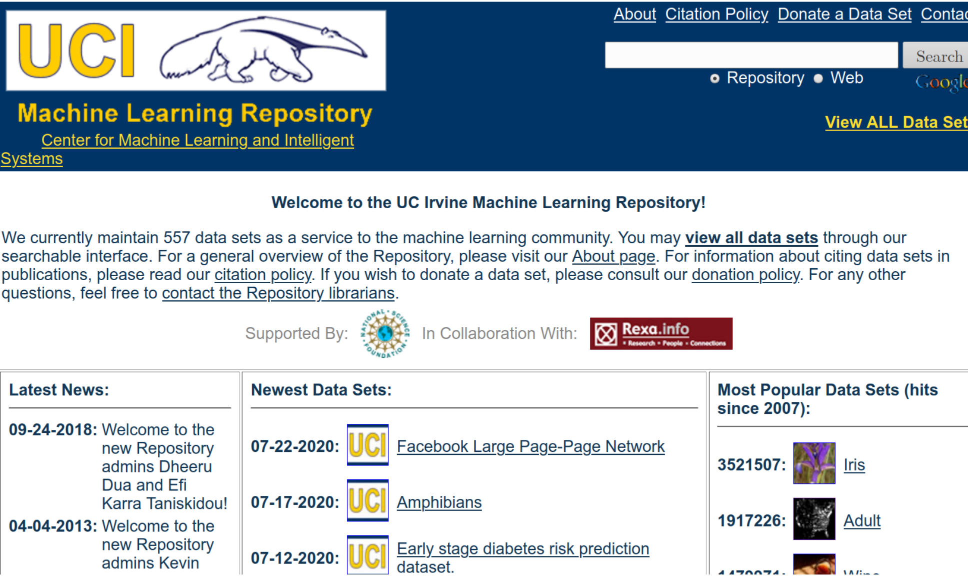
Dit datasæt fra f.eks. `https://www.kaggle.com...`

(brug min login: user=cef@ase.au.dk, password=test123)



Opg. L04 Beskrivelse af eget slutprojekt.pdf

..eller UCI `https://archive.ics.uci.edu/ml/index.php`..



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UCI

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Center for Machine Learning and Intelligent Systems

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Latest News:

09-24-2018: Welcome to the new Repository admins Dheeru Dua and Efi Karra Taniskidou!

04-04-2013: Welcome to the new Repository admins Kevin

Newest Data Sets:

07-22-2020: Facebook Large Page-Page Network

07-17-2020: Amphibians

07-12-2020: Early stage diabetes risk prediction dataset.

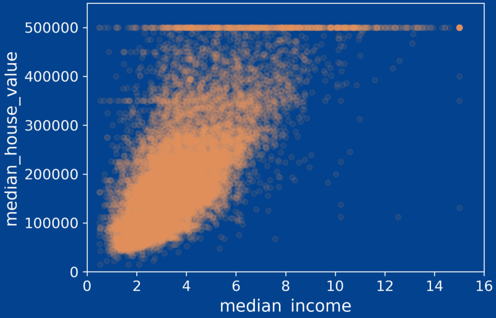
Most Popular Data Sets (hits since 2007):

3521507: Iris

1917226: Adult

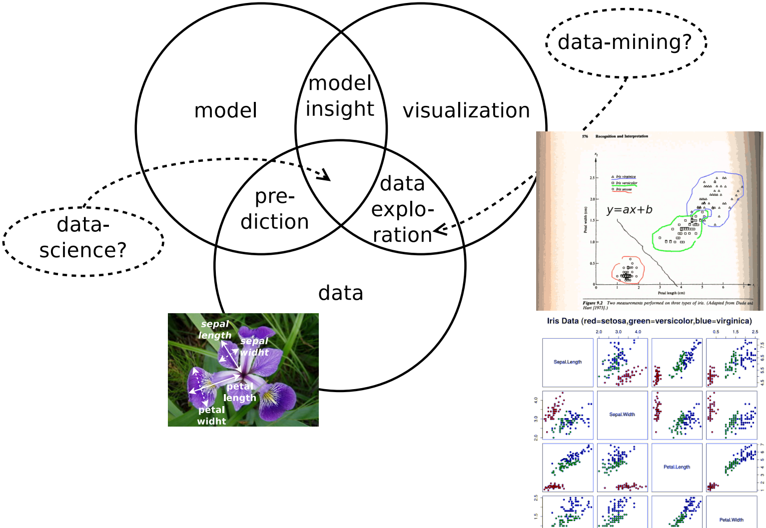
STATISTICS AND VISUALIZATION

μ, σ and being a Data Science Expert..



Machine learning baggrund

Machine learning: data science ekspert (fra L01)



Mean and Variance

The mean and variance (and hence the standard deviation) for a random variable X can for a population of N samples be estimated as

$$
\begin{aligned}
E[X] &= \tfrac{1}{N}\textstyle\sum_{i=1}^{N} X_i && = \mu_X \\[1em]
V[X] &= E[(X_i - E[X])(X_i - E[X])] \\
&= E[X_i X_i] - E[X]^2 \\
&= \left(\tfrac{1}{N}\textstyle\sum_{i=1}^{N} X_i X_i\right) - \mu_X^2 && = \sigma_X^2 \\[1em]
\sigma &= \sqrt{V}
\end{aligned}
$$

Notice that the $1/N$ factor most often appears as $1/(N-1)$ for the variance estimation.

When using the factor $1/(N-1)$, $\hat{V}$ is said to be the best unbiased estimator, when it is $1/N$ it will be biased, both assuming an underlying normal distribution.

Auto- and Cross-covariance

Now let's goto full matrix notation for the covariance. For a data matrix $\mathbf{X}$

$$\mathbf{X} = \begin{bmatrix} x_1^{(1)} & x_2^{(1)} & \cdots & x_d^{(1)} \\ x_1^{(2)} & x_2^{(2)} & \cdots & x_d^{(2)} \\ \vdots & & & \\ x_1^{(n)} & x_2^{(n)} & \cdots & x_d^{(n)} \end{bmatrix}$$

the previous one-dimensional random variable X can now be seen as a d-dimensional vector $\mathbf{x}^{(i)}$, that is one of the data rows in the full data matrix

$$X_i \rightarrow \mathbf{x}^{(i)} = \begin{bmatrix} x_1^{(i)} & x_2^{(i)} & \cdots & x_d^{(i)} \end{bmatrix}^T$$

Auto- and Cross-covariance

The (biased) auto–covariance matrix can be estimated as

$$
\begin{aligned}
E[\mathbf{X}] &= \mu_{\mathbf{X}} \\
&= \frac{1}{n}\sum_{i=1}^{n} \mathbf{x}^{(i)}
\end{aligned}
$$

$$
\begin{aligned}
\Sigma(\mathbf{X}) &= \mathrm{cov}(\mathbf{X}, \mathbf{X}) \\
&= \frac{1}{n}\sum_{i=1}^{n} \mathbf{x}^{(i)}\mathbf{x}^{(i)T} - \mu_{\mathbf{X}}\mu_{\mathbf{X}}^{T}
\end{aligned}
$$

with implicit $1/N$ factor here (inside the first $E[\cdot]$), so the definition is a biased covariance. You may opt to use the factor $1/(N-1)$ instead.

For yet another data matrix $\mathbf{Z}$ the (biased) cross-covariance matrix is given by

$$
\begin{aligned}
\Sigma(\mathbf{X}, \mathbf{Z}) &= \mathrm{cov}(\mathbf{X}, \mathbf{Z}) \\
&= \frac{1}{n}\sum_{i=1}^{n} \mathbf{x}^{(i)}\mathbf{z}^{(i)T} - \mu_{\mathbf{X}}\mu_{\mathbf{Z}}^{T}
\end{aligned}
$$

Covariance Matrix, binary classifier (SKIP slide!)

For a dataset, **X**; features cat and dog; classifying cat/dog

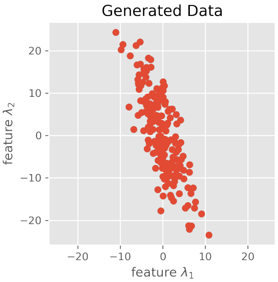
Covariance matrix (dim = features x features)

$$\Sigma(\mathbf{X}) = \begin{bmatrix} \sigma_{\text{cat,cat}} & \sigma_{\text{cat,dog}} \\ \sigma_{\text{dog,cat}} & \sigma_{\text{dog,dog}} \end{bmatrix} = \begin{array}{c|cc} & \text{cat} & \text{dog} \\ \hline \text{cat} & \sigma^2_{\text{cat}} & \sigma_{\text{cat,dog}} \\ \text{dog} & \sigma_{\text{dog,cat}} & \sigma^2_{\text{dog}} \end{array}$$

co-variance

$$\sigma_{\text{cat,dog}} = \frac{1}{n}\sum_{i=1}^{n}(x^{(i)}_{\text{cat}} - \mu_{\text{cat}})(x^{(i)}_{\text{dog}} - \mu_{\text{dog}})$$

Example $\quad \Sigma(\mathbf{X}) = \begin{bmatrix} 13.2 & -28.8 \\ -28.8 & 93.3 \end{bmatrix}$



Confusion matrix, cats only, cat/non-cat

(dim = classes x classes)

$$\mathbf{M} = \begin{bmatrix} \text{TP} & \text{FP} \\ \text{FN} & \text{TN} \end{bmatrix} = \begin{array}{c|cc} & \multicolumn{2}{c}{\textit{actual}} \\ & \text{cat} & \text{non-cat} \\ \hline \text{cat} & \text{T, cat} & \text{F, cat} \\ \text{dog} & \text{F, dog} & \text{T, non-cat} \end{array}$$

Looking for Correlations

..using the auto-covariance matrix,

	Grade 3	Grade 4	Grade 5	Grade 6	Grade 7	Grade 8
Grade 3	1.0000	0.7598	0.7199	0.6940	0.6869	0.6432
Grade 4	0.7598	1.004	0.7975	0.7675	0.7574	0.7189
Grade 5	0.7198	0.7975	0.9933	0.7813	0.7639	0.7218
Grade 6	0.6940	0.7675	0.7813	0.9899	0.7958	0.7579
Grade 7	0.6869	0.7574	0.7639	0.7958	0.9820	0.7884
Grade 8	0.6432	0.7189	0.7218	0.7579	0.7884	0.9826

..for regression: the standard correlation coefficient, Pearson's r,

Looking for Correlations

Since the dataset is not too large, you can easily compute the *standard correlation coefficient* (also called *Pearson's r*) between every pair of attributes using the corr() method:

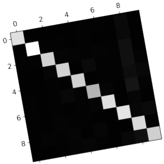
```
corr_matrix = housing.corr()
```

Now let's look at how much each attribute correlates with the median house value:

```
>>> corr_matrix["median_house_value"].sort_values(ascending=False)
median_house_value    1.000000
median_income         0.687170
total_rooms           0.135231
housing_median_age    0.114220
households            0.064702
total_bedrooms        0.047865
population           -0.026699
longitude            -0.047279
latitude             -0.142826
Name: median_house_value, dtype: float64
```

The correlation coefficient ranges from –1 to 1. When it is close to 1, it means that there is a strong positive correlation; for example, the median house value tends to go up when the median income goes up. When the coefficient is close to –1, it means that there is a strong negative correlation; you can see a small negative correlation

..or for classification: the confusion matrix



Data Science: Visualization

Take a Quick Look at the Data Structure

Let's take a look at the top five rows using the DataFrame's `head()` method (see Figure 2-5).

In [5]:
```
housing = load_housing_data()
housing.head()
```

Out[5]:

	longitude	lati
0	-122.23	37.
1	-122.22	37.
2	-122.24	37.
3	-122.25	37.
4	-122.25	37.

Figure 2-5. Top five rows in

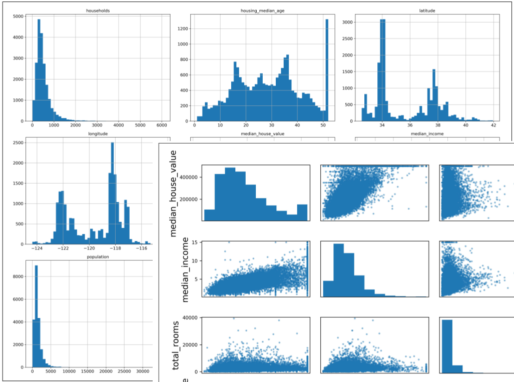


Figure 2-8. A histogram fo

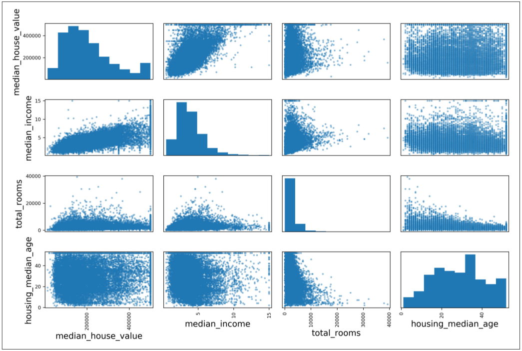


Figure 2-15. Scatter matrix

Data Science: Visualization

..why so many sales at `median_house_value` $= 350$ K\$ and 500 K\$??

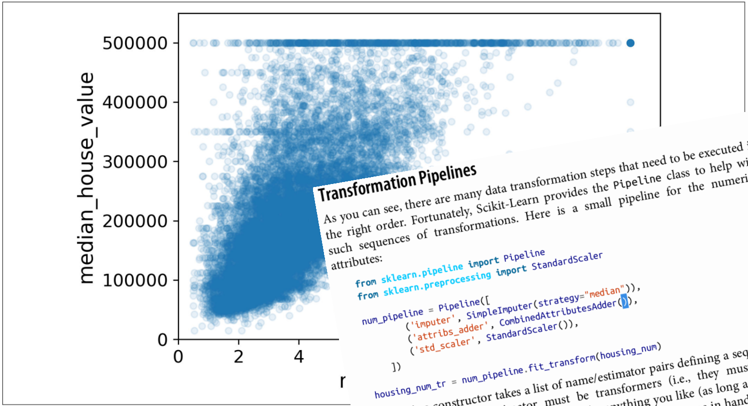


Figure 2-16. Median income versus media

Transformation Pipelines

As you can see, there are many data transformation steps that need to be executed in the right order. Fortunately, Scikit-Learn provides the `Pipeline` class to help with such sequences of transformations. Here is a small pipeline for the numerical attributes:

```
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler

num_pipeline = Pipeline([
        ('imputer', SimpleImputer(strategy="median")),
        ('attribs_adder', CombinedAttributesAdder()),
        ('std_scaler', StandardScaler()),
    ])

housing_num_tr = num_pipeline.fit_transform(housing_num)
```

The `Pipeline` constructor takes a list of name/estimator pairs defining a sequence of steps. All but the last estimator must be transformers (i.e., they must have a `fit_transform()` method). The names can be anything you like (as long as they are unique and don't contain double underscores "__"): they will come in handy later for hyperparameter tuning.

When you call the pipeline's `fit()` method, it calls `fit_transform()` sequentially on all transformers, passing the output of each call as the parameter to the next call, until it reaches the final estimator, for which it just calls the `fit()` method.

..fixing data via pipelines..

PIPELINES

Putting it all together in Python code...

Pipelines and Preprocessing of Data

Normalization via Scaling or Standardization

Why the need for preprocessing?

> *Standardization of datasets is a* **common requirement for many machine learning estimators** *[..]; they might* **behave badly** *if the individual features do not more or less look like standard normally distributed data. [..]*
>
> [`https://scikit-learn.org/stable/modules/preprocessing.html`]

Standardization of a feature vector $\mathbf{x}$, giving $\mathbf{x}'$ mean zero, and standard deviation one

$$\mathbf{x}' = \frac{\mathbf{x} - \mu_{\mathbf{x}}}{\sigma_{\mathbf{x}}}$$

What kind of estimators needs preprocessing?

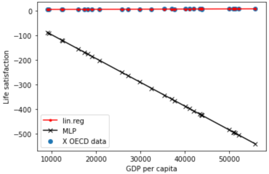
$\rightarrow$ **Neural networks (NNs) in particular!**

What is the difference between Standardization and Scaling?

Pipelinesand Polynomial Regression

Exercise: `pipelines.ipynb`: Revisit the OECD data in O1s for MLPs

Feature: GDP per capita feature in range 10K to 50K \$.
But MLP expects input in the range [0;1] or perhaps [-1;1].




```python
# Manual scaling..
X_min = np.min(X)
X_max = np.max(X)
s = X_max - X_min

print(f"X_min={X_min:.0f},  X_max={X_max:.0f},  s={s:.0f}")

X_scaled = (X-X_min)/s
print(f"X_scaled.shape={X_scaled.shape}")
print(f"np.min(X_scaled)={np.min(X_scaled)}")
print(f"np.max(X_scaled)={np.max(X_scaled)}")

mlp.fit(X_scaled ,y.ravel())
y_pred_mlp = mlp.predict((M-X_min)/s)

plt.plot(m, y_pred_lin, "r")
plt.plot(m, y_pred_mlp, "k")

print(f"mpl.score={mlp.score(X_scaled, y.ravel()):0.2f}")
```

```
Prints:
X_min=9055,
X_max=55805, s=46750
X_scaled.shape=(29, 1)
np.min(X_scaled)=0.0
np.max(X_scaled)=1.0
mpl.score=0.70
```

Pipelines

OECD Data and MLPs: introducing a `MinMaxScaler`

```python
# Now, do the same but via a pipeline..
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()
scaler.fit(X)
X_scaled = scaler.transform(X)
M_scaled = scaler.transform(M)

mlp.fit(X_scaled, y)
y_pred_mlp = mlp.predict(M_scaled)

print(f"mpl.score={mlp.score(X_scaled, y):0.2f}")

# PRINTS: mpl.score=0.71
```

Pipelines

OECD Data and MLPs: putting everything in a Full Pipeline

```python
# Or even better, in a full pipeline..
from sklearn.pipeline import Pipeline

pipe = Pipeline( # indent pipeline as VHDL port mappings!
  [
    ('scaler', MinMaxScaler()),
    ('mlp', mlp)
  ]
)

pipe.fit(X, y)

print(f"pipe.score(..)={pipe.score(X, y):0.2f}"

# PRINTS: pipe.score(..)=0.68
```

Pipelines and Polynomial Regression

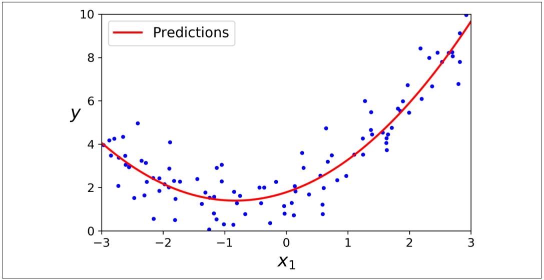


Figure 4-13. Polynomial Regression model predictions

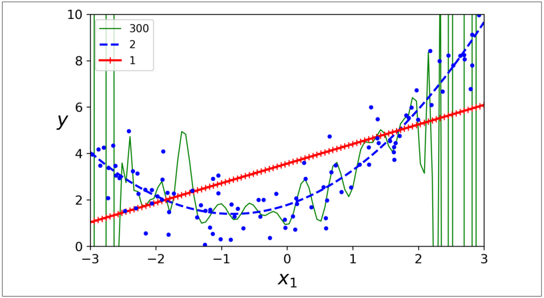


Figure 4-14. High-degree Polynomial Regression

Pipelines and Polynomial Regression

Python code from Opgave: L07/capacity_under_overfitting.ipynb

```
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import cross_val_score
..
polynomial_features = PolynomialFeatures(degree=degrees[i], ..
linear_regression = LinearRegression()

pipeline = Pipeline(
  [
    ("polynomial_features", polynomial_features),
    ("linear_regression", linear_regression)
  ]
)

pipeline.fit(X[:, np.newaxis], y)

scores = cross_val_score(
    pipeline, X[:, np.newaxis], y,
    scoring="neg_mean_squared_error", cv=10
  )
score_mean = -scores.mean()
```

Pipelines and K-fold CV

Evaluate a score by cross-validation: `cross_val_score(..)`

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scikit-learn 0.24.1
Other versions

Please **cite us** if you use the software.

`sklearn.model_selection.cross_val_score`
Examples using `sklearn.model_selection.cr`

`sklearn.model_selection`.cross_val_score

`sklearn.model_selection.`**`cross_val_score`**(*estimator*, *X*, *y=None*, ***, *groups=None*, *scoring=None*, *cv=None*, *n_jobs=None*, *verbose=0*, *fit_params=None*, *pre_dispatch='2*n_jobs'*, *error_score=nan*) [source]

Evaluate a score by cross-validation

Read more in the User Guide.

Parameters:

estimator : ***estimator object implementing 'fit'***
The object to use to fit the data.

X : ***array-like of shape (n_samples, n_features)***
The data to fit. Can be for example a list, or an array.

y : ***array-like of shape (n_samples,) or (n_samples, n_outputs), default=None***
The target variable to try to predict in the case of supervised learning.

groups : ***array-like of shape (n_samples,), default=None***
Group labels for the samples used while splitting the dataset into train/test set. Only used in conjunction with a "Group" cv instance (e.g., `GroupKFold`).

scoring : ***str or callable, default=None***
A str (see model evaluation documentation) or a scorer callable object / function with signature `scorer(estimator, X, y)` which should return only a single value.

Similar to `cross_validate` but only a single metric is permitted.

If None, the estimator's default scorer (if available) is used.

cv : ***int, cross-validation generator or an iterable, default=None***