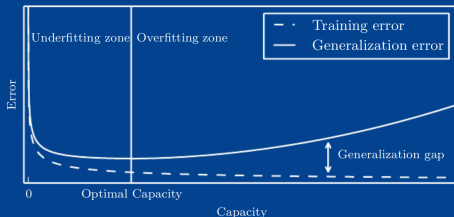




## LESSON 8: Model-capacity, Under- and Overfitting, Generalization

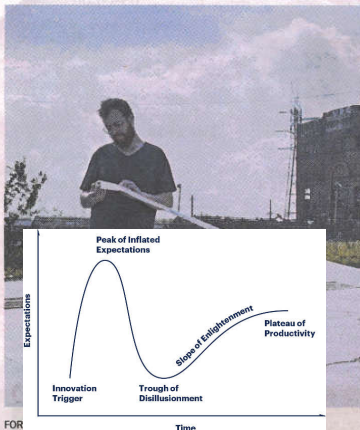
CARSTEN EIE FRIGAARD

SPRING 2020









# På roadtrip med en insekthjerne

AF MIKKEL BORIS

I 2016 slog computeren AlphaGo den 18-dobbelte verdensmester i brætspil Go, Lee Sedol. Go er et kompliceret og abstrakt spil, som kræver intuition og kreativitet, men den kunstige intelligens vandt med en række innovative træk overlegen. Underveis i spillet troede kommentatorerne

Goodwin til Weekendavisen fra sin lejlighed i Los Angeles.

Inden køreturen havde han brugt måneder på at træne maskinen. Han satte den til at læse et stort korpus af moderne litteratur fra hele verden, så den kunne lære at skrive af de store forfattere.

»Det fungerer ligesom autokorrektur på din telefon, bare klogere og trænet på en mere litterær kilde. Den skriver bogstav for bogstav, så den har lært sig selv at forudsige det næste

når du dekonstruerer dem. Efter at have læst den i ét stræk og fået turen lidt på afstand har romanen fået en universallitet, så jeg kan projicere mine egne oplevelser ind i teksten,« uddyber Goodwin.

– Du har beskrevet projektet som at lære en insekthjerne at skrive. Hvad betyder det?

»Jeg forsøgte at pointere, at maskinen ikke er på niveau med den menneskelige hjerne. Et artificielt neuralt net er en algoritme, der er lavet, som vi tror, hjernen fungerer. Leo synes

»Det er et forsøg på at skabe en ny brugerflade for at skrive. På en måde har jeg jo skrevet en roman med en bil,« fortæller Ross Goodwin om sin AI-forfattede bog *The Road*



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front

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front

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# A computer vision system to monitor the infestation level of Varroa destructor in a honeybee colony

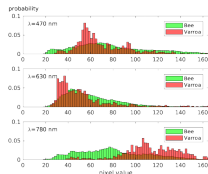


Figure 5: Histograms of bee and varroa pixel intensity values, for the spectral wavelengths 470 nm, 630 nm, and 780 nm respectively, recorded with the JAI camera. The image path is via the mirror-window-mirror, i.e. data were sampled with the setup given in figure 4. The image data for the histogram is the single bee with mate seen in figure 6.

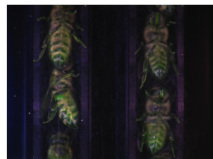


Figure 6: The actual unprocessed camera view of the bees

spectively. The CM analysis was able to rank all wavelengths combinations, using one, two, three or four distinct wavelengths to give a ranking list of 'best' combination also taking the JAI camera spectrum into account.

The CM value of the actual choose wavelengths combination (470-630-780 nm) gave a rank just below the CM average score. This CM analysis was conducted after picking the actual used wavelengths, so later versions of the VMU might want to investigate a CM combination with a higher rank.

A specially designed diffuser and a number of narrow spectral LEDs were mounted in the camera focus illuminating the bees.

Figure 7 displays along the passage, with the green with the NIR

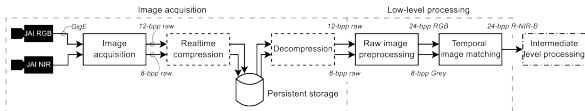


Figure 7: The low-level image processing pipeline. Raw camera images are stored on disk for later retrieval and post-processing. 12- and 8 bits-per-pixel are used as the raw JAI/Bayer packed pixel format for the RGB and IR images respectively. Lossless, real-time compression can be introduced if persistent storage bandwidth is less than the raw-stream image rate of 93 MiB/sec. The 12- and 8-bpp raw images from the network arrives out-of-order with respect to each other, hence the need for the temporal image matching.

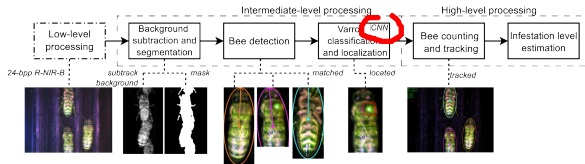


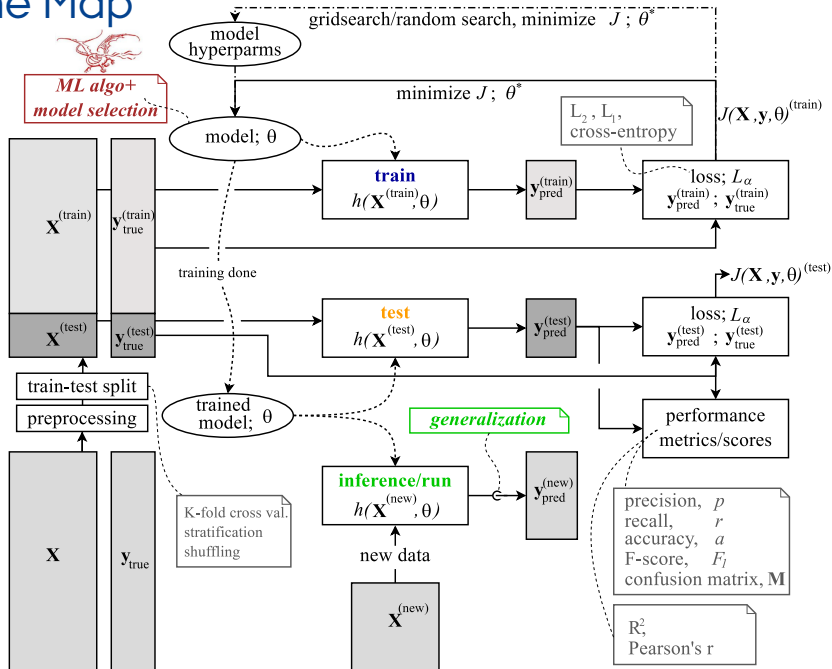
Figure 8: The processing pipeline of the intermediate- to high-level image processing algorithms to analyze and count the number of bees with *Varroa destructor*. A trained convolutional neural network (CNN) was used for the Varroa classification and localization stage.



# BA Project: generic tagging/labelling tool



# The Map





# Pipelines

Brief intro to Scikit-learn pipelines..

Python code from `capacity_under_overfitting.ipynb`

```
1  from sklearn.pipeline import Pipeline
2  from sklearn.preprocessing import PolynomialFeatures
3  from sklearn.linear_model import LinearRegression
4  from sklearn.model_selection import cross_val_score
5
6  ..
7
8  polynomial_features = PolynomialFeatures(degree=degrees[i], ..
9  linear_regression = LinearRegression()
10
11  pipeline = Pipeline([
12      ("polynomial_features", polynomial_features),
13      ("linear_regression", linear_regression)
14  ])
15  pipeline.fit(X[:, np.newaxis], y)
16
17  scores = cross_val_score(pipeline, X[:, np.newaxis], y, scoring=
18      "neg_mean_squared_error", cv=10)
19  ..
20  score_mean = -scores.mean()
```

# RESUMÉ: L02/performance\_metrics.ipynb

## Classification metrics

See the [Classification metrics](#) section of the user guide for further details.

<code>metrics.accuracy_score</code> ( <i>y_true</i> , <i>y_pred</i> [, ...])	Accuracy classification score.
<code>metrics.auc</code> ( <i>x</i> , <i>y</i> [, <i>reorder</i> ])	Compute Area Under the Curve (AUC) using the trapezoidal rule
<code>metrics.average_precision_score</code> ( <i>y_true</i> , <i>y_score</i> )	Compute average precision (AP) from prediction scores
<code>metrics.cohen_kappa_score</code> ( <i>y1</i> , <i>y2</i> [, <i>labels</i> , ...])	Cohen's kappa: a statistic that measures inter-annotator agreement.
<code>metrics.confusion_matrix</code> ( <i>y_true</i> , <i>y_pred</i> [, ...])	Compute confusion matrix to evaluate the accuracy of a classification
<code>metrics.f1_score</code> ( <i>y_true</i> , <i>y_pred</i> [, <i>labels</i> , ...])	Compute the F1 score, also known as balanced F-score or F-measure
<code>metrics.log_loss</code> ( <i>y_true</i> , <i>y_pred</i> [, <i>eps</i> , ...])	Log loss, aka logistic loss or cross-entropy loss.
<code>metrics.precision_score</code> ( <i>y_true</i> , <i>y_pred</i> [, ...])	Compute the precision
<code>metrics.recall_score</code> ( <i>y_true</i> , <i>y_pred</i> [, ...])	Compute the recall
<code>metrics.roc_auc_score</code> ( <i>y_true</i> , <i>y_score</i> [, ...])	Compute Area Under the Receiver Operating Characteristic Curve (ROC AUC) from prediction scores.
<code>metrics.roc_curve</code> ( <i>y_true</i> , <i>y_score</i> [, ...])	Compute Receiver operating characteristic (ROC)
<code>metrics.zero_one_loss</code> ( <i>y_true</i> , <i>y_pred</i> [, ...])	Zero-one classification loss.

## Regression metrics

See the [Regression metrics](#) section of the user guide for further details.

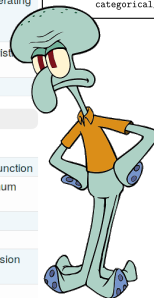
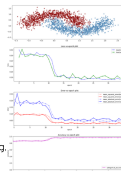
<code>metrics.explained_variance_score</code> ( <i>y_true</i> , <i>y_pred</i> )	Explained variance regression score function
<code>metrics.max_error</code> ( <i>y_true</i> , <i>y_pred</i> )	max_error metric calculates the maximum residual error.
<code>metrics.mean_absolute_error</code> ( <i>y_true</i> , <i>y_pred</i> )	Mean absolute error regression loss
<code>metrics.mean_squared_error</code> ( <i>y_true</i> , <i>y_pred</i> [, ...])	Mean squared error regression loss
<code>metrics.mean_squared_log_error</code> ( <i>y_true</i> , <i>y_pred</i> )	Mean squared logarithmic error regression loss
<code>metrics.median_absolute_error</code> ( <i>y_true</i> , <i>y_pred</i> )	Median absolute error regression loss
<code>metrics.r2_score</code> ( <i>y_true</i> , <i>y_pred</i> [, ...])	R^2 (coefficient of determination) regression

## Notes on Keras MLPs

Typical Keras MLP Supervised Classifier setup.

- ▶ loss function  
`loss='categorical_crossentropy'`
- ▶ metrics collected via history  
`metrics=['categorical_accuracy', 'mean_squared_error', 'mean_absolute_error']`
- ▶ input lay.: categorical encoding.
- ▶ output lay.: softmax function.

And notice that Keras **do not** provide metrics like precision, recall, F1 but instead `categorical_accuracy`, `binary_accuracy`



# Model capacity

Exercise: `capacity_under_overfitting.ipynb`

Dummy and Paradox classifier:

*capacity* fixed  $\sim 0$ , cannot generalize at all!

Linear regression for a polynomial model:

*capacity*  $\sim$  degree of the polynomial,  $x^n$

Neural Network model:

*capacity*  $\propto$  number of neurons/layers

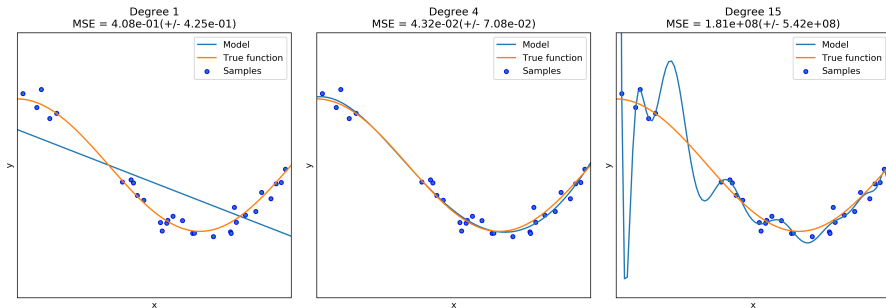
$\Rightarrow$  **Capacity** can be hard to express as a quantity for some models, but you need to choose..

$\Rightarrow$  how to choose the **optimal capacity**?

# Under- and overfitting

Exercise: `capacity_under_overfitting.ipynb`

Polynomial linear reg. fit for underlying model:  $\cos(x)$



- ▶ underfitting: capacity of model too low,
- ▶ overfitting: capacity too high.

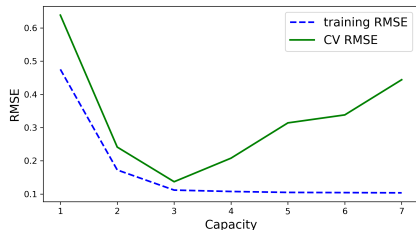
⇒ how to choose the **optimal** capacity?

# Generalization Error

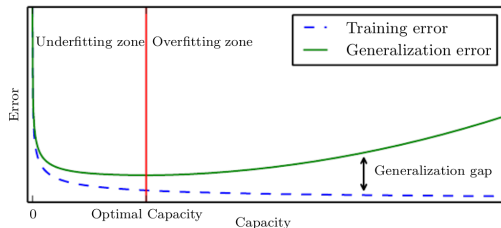
Exercise: `generalization_error.ipynb`

RMSE-capacity plot for lin. reg. with polynomial features

(capacity  $\sim$  degree of poly)



(Figure 5.3 from [DL])



Inspecting the plots from the exercise (`.ipynb`) and [DL],  
extracting the concepts:

- ▶ training/generalization error,
- ▶ generalization gap,
- ▶ underfit/overfit zone,
- ▶ optimal capacity (best-model, early stop),
- ▶ (and the two axes: x/capacity, y/error.)

# Generalization Error

Exercise: `generalization_error.ipynb`

NOTE: three methods/plots:

- i) via **learning curves** as in [HOML],
- ii) via an **error-capacity** plot as in [GITHOML] and [DL],
- ii) via an **error-epoch** plot as in [GITHOML].

