Computer Vision: scikit-learn and opencv

Artificial Intelligence @ Allegheny College

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Computer Vision

Make computers understand images and video.

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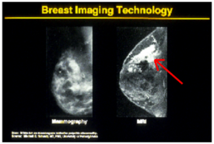
Make computers understand images and video

Computer Vision

- What kind of scene?
- Where are the cars?
- How far is the building?

Why computer vision matters?

Safety

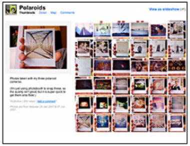


Health

Security

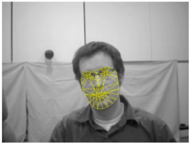
Comfort

Fun

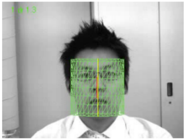


Access

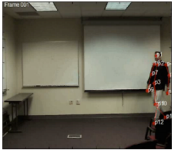
Applications of Computer Vision



“Face Recognition”



“Pose Estimation”



“Body Tracking”

“Speech Reading”

“Palm Recognition”

“Car Tracking”

OpenCV

- An open source BSD licensed computer vision library
  - Patent-encumbered code isolated into “non-free” module (SIFT, SURF, some of the Face Detectors, etc.)
- Available on all major platforms
  - Android, iOS, Linux, Mac OS X, Windows
- Written primarily in C++
  - Bindings available for Python, Java, even MATLAB (in 3.0).
- Well documented at `http://docs.opencv.org`
- Source available at `https://github.com/Itseez/opencv`

OpenCV

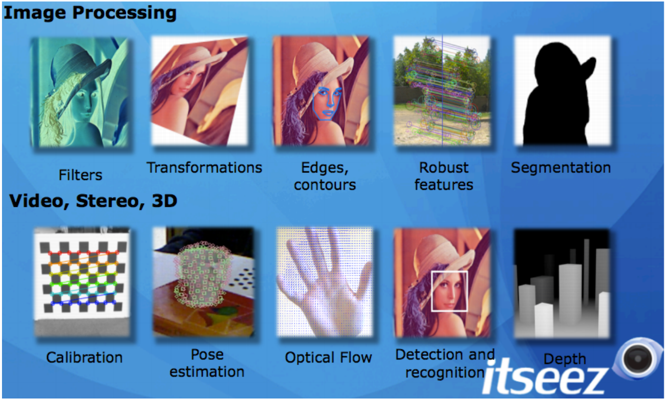


Image Processing
Filters
Transformations
Edges, contours
Robust features
Segmentation
Video, Stereo, 3D
Calibration
Pose estimation
Optical Flow
Detection and recognition
Depth
itseez

OpenCV: Pixel

- Grayscale: each pixel has a value between 0 (black) and 255 (white) - values between 0 and 255 are varying shades of gray.

OpenCV: Pixel

- Grayscale: each pixel has a value between 0 (black) and 255 (white) - values between 0 and 255 are varying shades of gray.
- Color: pixels are normally represented in the RGB color space
  - one value for the Red component, one for Green, and one for Blue,
  - each of the three colors is represented by an integer in the range 0 to 255,
  - how "much" of the color there is.

OpenCV: Coordinate System

- The point (0, 0) corresponds to the upper left corner of the image
- x value increases as we move to the right
- y value increases as we move down

OpenCV: Image Representation

- OpenCV represents images as `NumPy` arrays (matrices).
- `NumPy` is a library for the Python programming language that provides support for large, multi- dimensional arrays.
- To access a pixel value, we need to supply the x and y coordinates of the pixel.
- OpenCV actually stores RGB values in the order of Blue, Green, and Red.

Images

How to input or output an image?

Images

How to input or output an image?

Load Image
Read image from disk.

`cv::imread(filename,0/1);`

0: read as grayscale image
1: read as color image

Save Image
Write image to disk.

`cv::imwrite(filename,im);`

Visualize Image
Show image in a window.

`cv::imshow(title,im);`

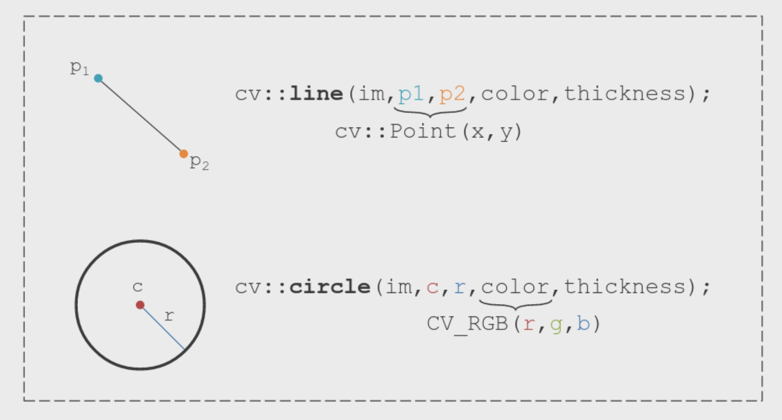
Note: if CV_32FC1, the gray value range is 0 to 1. Everything above 1 is white and everything below 0 is black.

Waitkey
Waits n milliseconds for user input.

`cv::waitkey(n);`

If n == -1, it waits forever.
Note: There must be a waitkey to show the image.

Drawing Primitives



Drawing Primitives

```
rectangle = np.zeros((300, 300), dtype = "uint8")
cv2.rectangle(rectangle, (25, 25), (275, 275), 255, -1)
```

Bitwise Operations

- `cv2.bitwise_and` (used in masking example): if both pixels have a value>0, the output pixel is set to 255 in the output image, otherwise it is 0.
- `cv2.bitwise_or`: if either of the pixels have a value>0, the output pixel is set to 255 in the output image, otherwise it is 0.
- `cv2.bitwise_xor`: same as `OR`, with a restriction: both pixels are not allowed to have values >0.
- `cv2.bitwise_not`: pixels with a value of 255 become 0, pixels with a value of 0 become 255.

scikit-learn

- Popular Python machine learning library
- Designed to be a well documented and approachable for non-specialist
- Built on top of NumPy and SciPy
- `scikit-learn` can be easily installed with pip or conda

  ```
  pip install scikit-learn
  conda install scikit-learn
  ```

Data representation in scikit-learn

- Training dataset is described by a pair of matrices, one for the input data and one for the output.
- Most commonly used data formats are a NumPy `ndarray` or a Pandas `DataFrame / Series`.

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- Most commonly used data formats are a NumPy `ndarray` or a Pandas `DataFrame / Series`.
- Each row of these matrices corresponds to one sample of the dataset.
- Each column represents a quantitative piece of information that is used to describe each sample (called "features").

Data representation in scikit-learn

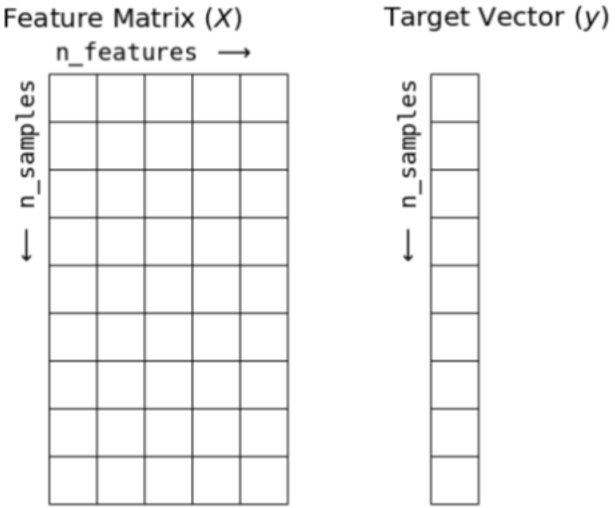


image credit: James Bourbeau

Features in scikit-learn

`feature` **Module**

`https://scikit-image.org/docs/dev/api/skimage.feature.html`

Histograms

- Histograms are collected counts of data organized into a set of predefined bins.

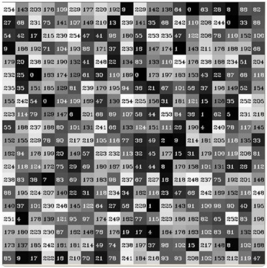


image credit:

https://docs.opencv.org/3.4/d8/dbc/tutorial_histogram_calculation.html

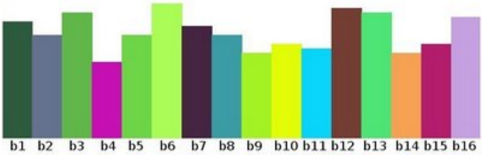
- We can segment our range in subparts (called bins) like:

$$[0, 255] = [0, 15] \cup [16, 31] \cup .... \cup [240, 255]$$

$$range = bin_1 \cup bin_2 \cup .... \cup bin_n = 15$$

Histograms

- We can keep count of the number of pixels that fall in the range of each bin.
- Applying this, we get the image below (axis x represents the bins and axis y the number of pixels in each of them).



- A histogram can keep count of not only of color intensities, but of whatever image features that we want to measure (i.e. gradients, directions, etc).

Estimators in scikit-learn

- Algorithms are implemented as **estimator** classes in `scikit-learn`.
- Each estimator in scikit-learn is extensively documented (e.g. the KNeighborsClassifier documentation) with API documentation, user guides, and example usages.
- A **model** is an instance of one of these estimator classes

Training a model

fit then predict

```
# Fit the model
model.fit(X, y)

# Get model predictions
y_pred = model.predict(X)
```

Decision Tree in scikit-learn

```
from sklearn.tree import DecisionTreeClassifier

clf = DecisionTreeClassifier(max_depth=2)
clf.fit(X, y)
```

```
DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=2,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=None,
            splitter='best')
```

image credit: James Bourbeau

Model performance metrics

- Many commonly used performance metrics are built into the metrics subpackage in scikit-learn.
- However, a user-defined scoring function can be created using the `sklearn.metrics.make_scorer` function.

```
# Classification metrics
from sklearn.metrics import (accuracy_score, precision_score,
                             recall_score, f1_score, log_loss)
# Regression metrics
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
```

```
y_pred = [0, 2, 1, 3, 1]
y_true = [0, 1, 1, 3, 2]
```

```
accuracy_score(y_true, y_pred)
```

```
0.6
```

```
mean_squared_error(y_true, y_pred)
```

```
0.4
```

Separate training and testing sets

- scikit-learn has a convenient train_test_split function that randomly splits a dataset into a testing and training set.

```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
                                                    random_state=2)

print(f'X.shape = {X.shape}')
print(f'X_test.shape = {X_test.shape}')
print(f'X_train.shape = {X_train.shape}')
```

```
X.shape = (150, 2)
X_test.shape = (30, 2)
X_train.shape = (120, 2)
```

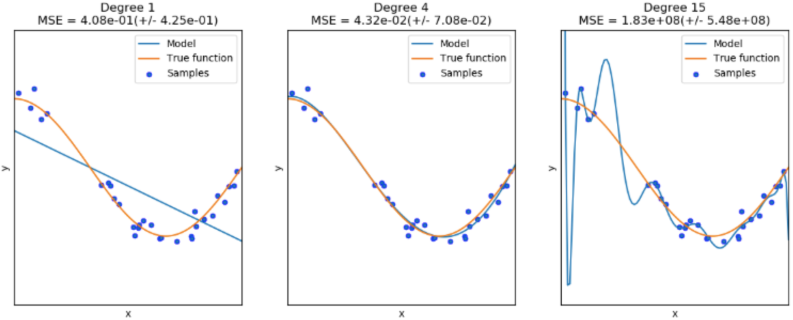
image credit: James Bourbeau

Model selection - hyperparameter optimization

- Model **hyperparameter** values (parameters whose values are set before the learning process begins) can be used to avoid under- and over-fitting.

Model selection - hyperparameter optimization

- Model **hyperparameter** values (parameters whose values are set before the learning process begins) can be used to avoid under- and over-fitting.
- **Under-fitting** - model isn't sufficiently complex enough to properly model the dataset at hand.
- **Over-fitting** - model is too complex and begins to learn the noise in the training dataset.



k-fold cross validation

- **Cross-validation** is a resampling procedure used to evaluate machine learning models on a limited data sample.
- It uses a limited sample in order to estimate how the model is expected to perform in general when used to make predictions on data not used during the training of the model.
- The parameter **k** refers to the number of groups that a given data sample is to be split into.

k-fold cross validation

1. Shuffle the dataset randomly.
2. Split the dataset into k groups.
3. For each unique group:
   3.1. Take the group as a hold out or test data set.
   3.2. Take the remaining groups as a training data set.
   3.3. Fit a model on the training set and evaluate it on the test set.
   3.4. Retain the evaluation score and discard the model.
4. Summarize the skill of the model using the sample of model evaluation scores.

k-fold cross validation

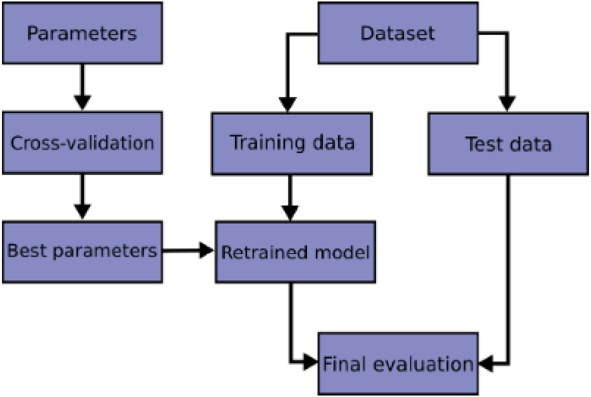


image credit:

`https://scikit-learn.org/stable/modules/cross_validation.html`

k-fold cross validation

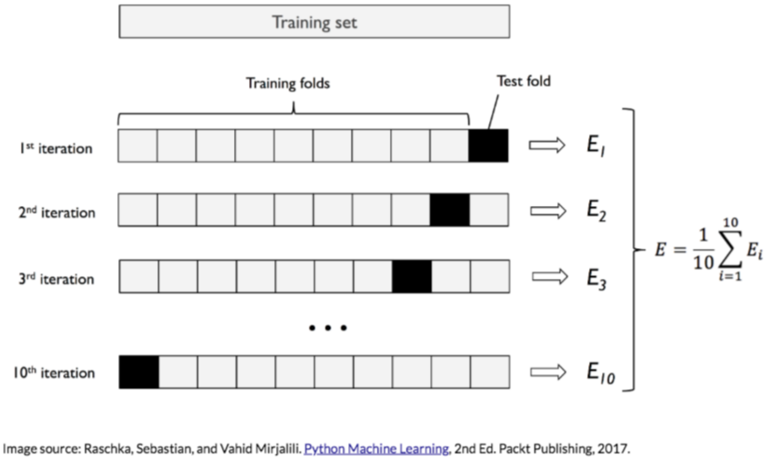


image credit:

James Bourbeau

Cross Validation in scikit-learn

```python
from sklearn.model_selection import cross_validate

clf = DecisionTreeClassifier(max_depth=2)
scores = cross_validate(clf, X_train, y_train,
                        scoring='accuracy', cv=10,
                        return_train_score=True)

print(scores.keys())
test_scores = scores['test_score']
train_scores = scores['train_score']
print(test_scores)
print(train_scores)

print('\n10-fold CV scores:')
print(f'training score = {np.mean(train_scores)} +/- {np.std(train_scores)}')
print(f'validation score = {np.mean(test_scores)} +/- {np.std(test_scores)}')
```

```
dict_keys(['fit_time', 'score_time', 'test_score', 'train_score'])
[0.78571429 0.64285714 0.83333333 0.66666667 1.         0.91666667
 0.54545455 0.72727273 0.81818182 0.72727273]
[0.79245283 0.79245283 0.76851852 0.80555556 0.75       0.77777778
 0.79816514 0.79816514 0.78899083 0.79816514]

10-fold CV scores:
training score = 0.787024375076132 +/- 0.016054059411612778
validation score = 0.7663419913419914 +/- 0.12718955265834164
```

image credit:

James Bourbeau