

# Model Selection and Evaluation

Dogs, Fried Chicken or Blueberry Muffins?

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# Model Selection and Evaluation

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# 1. Problem description



Dogs, Fried Chicken or  
Blueberry Muffins?

- **image classification:** the task of **extracting information classes** from a multiband raster image.
- **multiclass classification:** classifying instances into one of three or more classes.

# 2. Model selection

## 2.1 Terminology

- **Hypothesis/model:** a certain function that we believe (or hope) is **similar to** the true function, the **target function** that we want to model.
- **Learning algorithm:** a set of **instructions** that tries to **model the target function** using our training dataset.
- **Classifier:** a **hypothesis** or **discrete-valued function** which is used to assign (categorical) class labels to particular data points.
- **Hyperparameters:** **tuning parameters** of a machine learning algorithm.  
(while **model parameters** are the parameters that a learning algorithm **fits** to the training data)

# 2. Model selection

## 2.2 feature extraction

- **ORB(Oriented FAST and Rotated BRIEF)**: a fusion of **FAST keypoint detector** and **BRIEF descriptor** with many modifications to enhance the performance.
- **SIFT(Scale Invariant Feature Transform)**: local and based on the appearance of the object at particular **interest points**, and are **invariant to image scale and rotation**.
- **SURF(speeded up robust features)**: based on the similar principles and steps as SIFT; algorithm contains three main steps: **interest point detection**, **local neighborhood description** and **matching**.

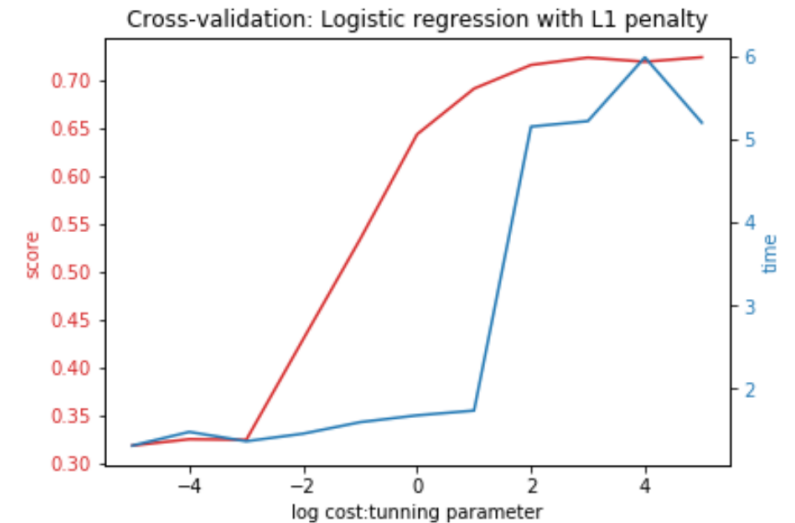
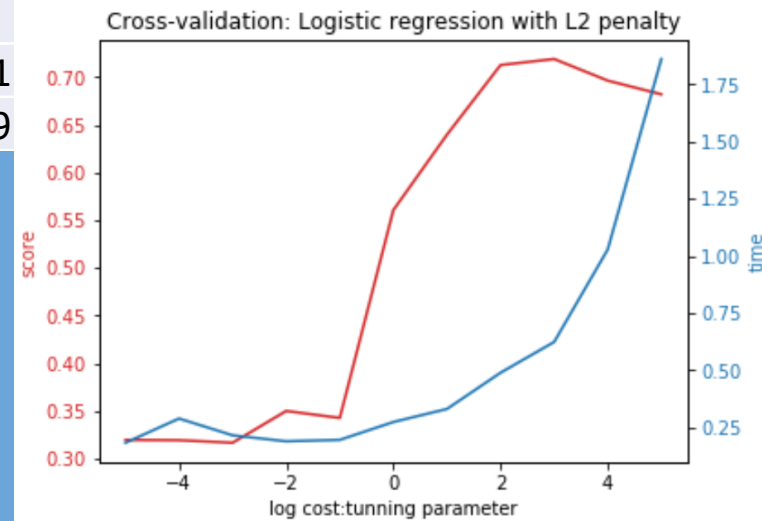
# 2. Model selection

## 2.3 basic model comparison

feature	model		
	Logistic	QDA	LDA
SIFT	0.5827	0.3327	0.491
RGB	0.6407	0.553	0.579

### Optimal Logistic Model:

- ORG feature
- L2 penalty
- Linear method
- Cost = 1000
- **Performance:** 5-fold-CV score: 0.8147 ; running time per round: 1.5828s.



# 2. Model selection

## 2.4 Alternative advanced model

### 2.4.1 SVM (Linear/RBF kernel)

- **Description**

**Supervised** learning models which constructs a hyperplane or set of hyperplanes in a high- or infinite-dimensional space.

- **Advantage**

**Effective** in high-dimensional spaces, even when  $\dim(n) > p$

**Memory effective**: only depend on support vectors

**Versatile**: different **Kernel functions** can be specified for different decision functions

- **Weakness**

Risk of **overfitting** when  $n \gg p$

**Calculation expensiveness**: calculated using 5-fold CV

# 2. Model selection

## 2.4 Alternative advanced model

### 2.4.2 XGBoost (Extreme Gradient Boosting)

- **Description**

An **advanced** implementation of gradient boosting algorithm by adding new models **sequentially** until no further improvement is achieved.

- **Advantage**

**Regularization**: 'regularized boosting' technique, helps to reduce overfit.

**Parallel Processing**: fast computations

**High flexibility**: allow to define custom optimization objectives and evaluation criteria.

Have in-built routine to **handle missing values**

- **Weakness**

Risk of **overfitting** when not having enough data



# 2. Model selection

## 2.4 Alternative advanced model

### 2.4.3 CNN (MobileNet)

- **Description**

“Vision begins with eyes, but truly takes place in the brain.”

Mostly based on an **artificial neural network**; using a cascade of **multiple layers** of **nonlinear** processing units for feature extraction and transformation .

- **Advantage**

**High performance** with enough data

**Time efficient**: reduces the need for feature engineering

**Universality**: can be adapted to new problems relatively easily

- **Weakness**

Extremely **computationally expensive** to train

Without strong theoretical foundation, hard to comprehend

# 3. Model assessment and comparison

## 3.1. Cost evaluation

- feature dimensions

RGB: 5\*5\*5    SIFT: 2000    MobileNet: 256\*256\*3

- model running time ( cross validation/training/prediction time)

XGBoost (9675.41s/1.46s/0.04s)

SVM (Linear 0.41/3.18/0.40s   RBF 2.59/2.45/0.33s)

CNN ( resize 118.69/548.78/22.68s)

## 3.2 Performance evaluation

- Accuracy

Baseline	SVM(linear)	SVM(RBF kernal)	XGBoost(RGB feature)	XGBoost(SIFT feature)	MobileNet
0.883	0.589	0.742	0.889	0.678	0.993

# 4. Model improvement and prospect

## 4.1 Model improvement

### 4.1.1 Advanced feature

- SIFT

**Invariant** to image scale and rotation.

**Robust** to changes in illumination, noise, and minor changes in viewpoint.

**Highly distinctive**, relatively easy to extract and allow for correct object identification with low probability of mismatch.

- RGB (more relevant to the classification problem characteristics)



**Gradient-based features**: makes the scheme robust to illumination variations whereas use of orientation information to define features provides robustness against contrast variations.

# 4. Model improvement and prospect

## 4.1 Model improvement

### 4.1.2 Parameter tuning

- SVM model

Linear: cost: (0.0001,0.001,**0.1**,1)

RBF: cost: (0.0001,0.001,**0.1**,1) ; gamma: (0.01,0.1,1,**10**,100)

- XGBoost model

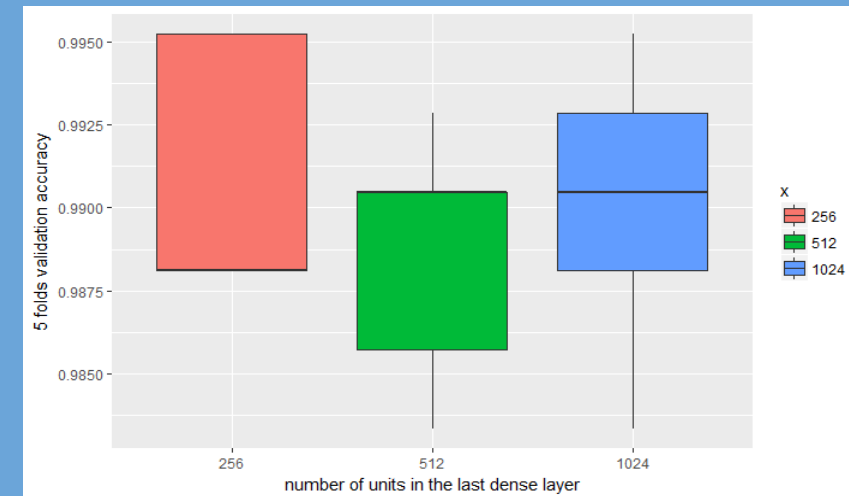
General Parameters

**Booster Parameters** (eta = 0.15, max\_depth = 4)

Learning Task Parameters

- CNN(mobile net)

Number of units in the last dense layer: 256



$M$ 

Model	Size	Top-1 Accuracy	Top-5 Accuracy	Parameters	Depth
Xception	88 MB	0.790	0.945	22,910,480	126
VGG16	528 MB	0.715	0.901	138,357,544	23
VGG19	549 MB	0.727	0.910	143,667,240	26
ResNet50	99 MB	0.759	0.929	25,636,712	168
InceptionV3	92 MB	0.788	0.944	23,851,784	159
InceptionResNetV2	215 MB	0.804	0.953	55,873,736	572
MobileNet	17 MB	0.665	0.871	4,253,864	88
DenseNet121	33 MB	0.745	0.918	8,062,504	121
DenseNet169	57 MB	0.759	0.928	14,307,880	169
DenseNet201	80 MB	0.770	0.933	20,242,984	201

(c)  $1 \times 1$  Convolutional Filters called Pointwise Convolution in the context of Depthwise Separable Convolution

# 4. Model improvement and prospect

## 4.2 Prospect

### 4.2.1 Potential problem

Independence of SIFT feature contradicts the requirement of cross validation.

### 4.2.2 Further improvement

Standardization

More indicators besides accuracy  
(ROC curve, gams & lift charts etc)



# 5. Reference

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Q&A



Thanks for listening.