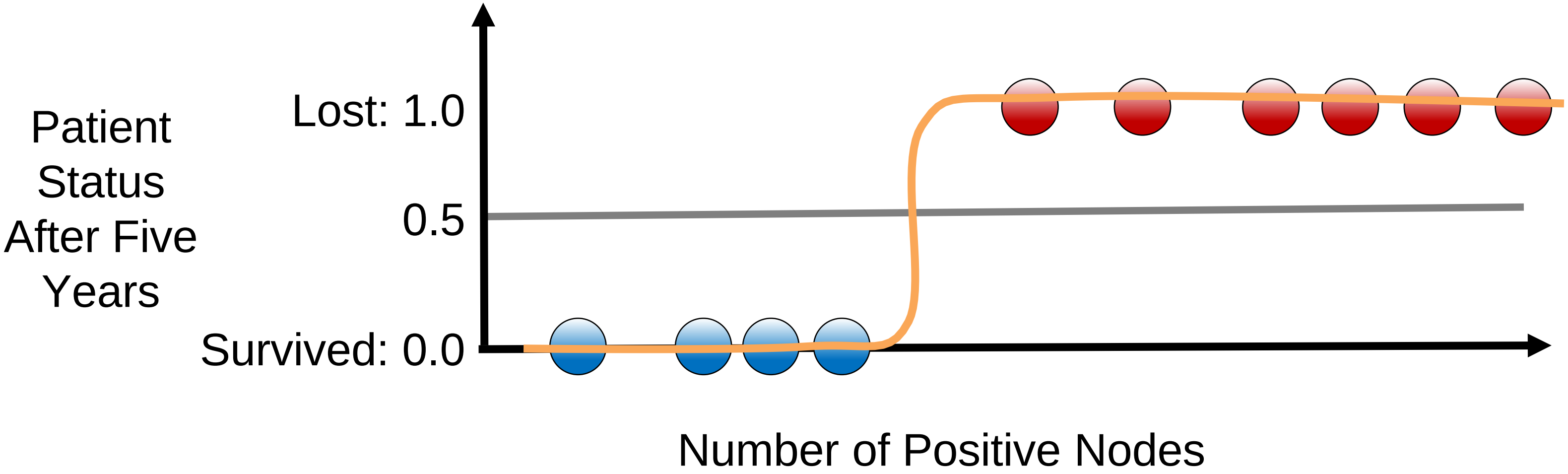
Chapter 7

Support Vector Machines Kernels

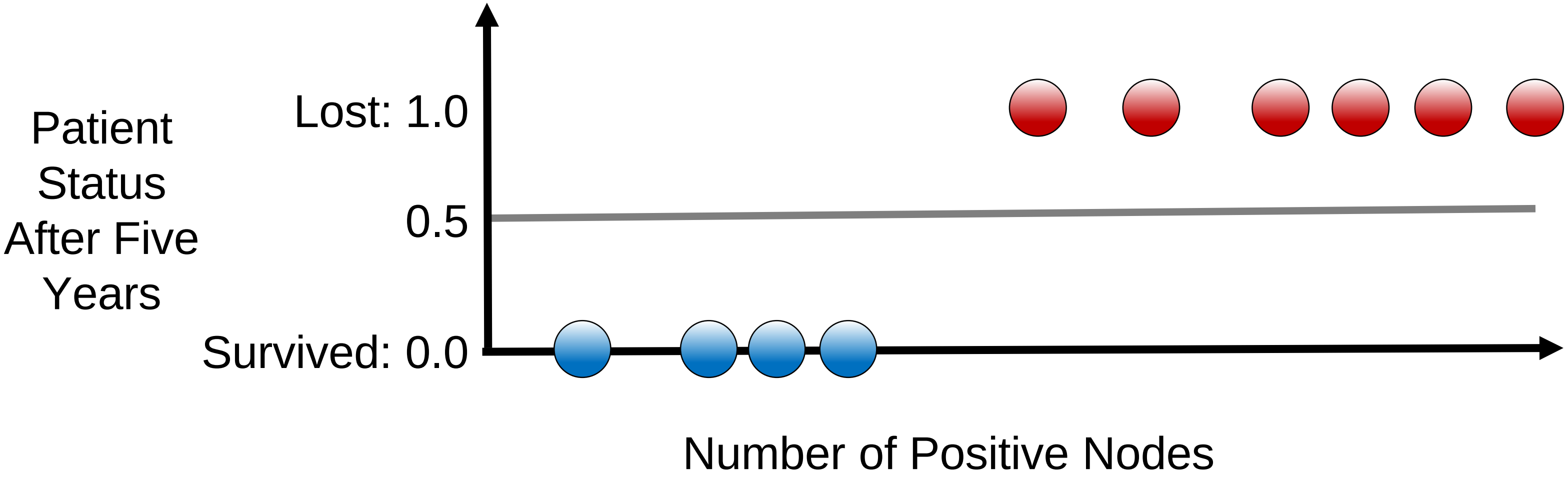
Support Vector Machines

Relationship to Logistic Regression

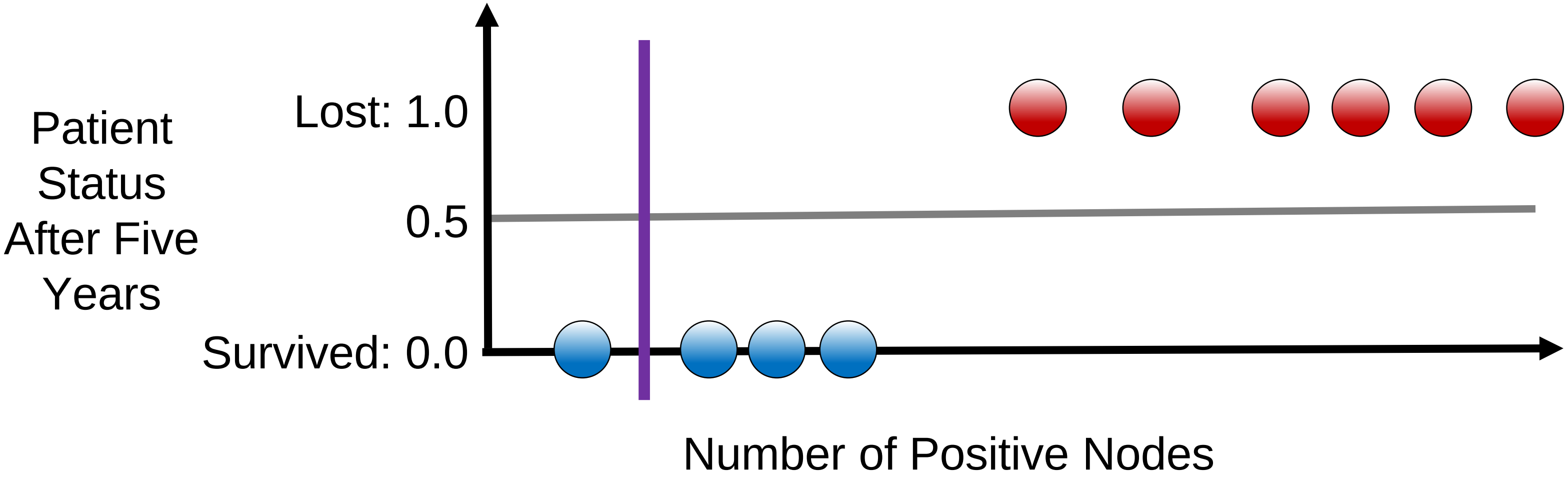


$$y_\beta(x) = \frac{1}{1+e^{-(\beta_0 + \beta_1 x + \varepsilon\ )}}$$

Support Vector Machines (SVM)

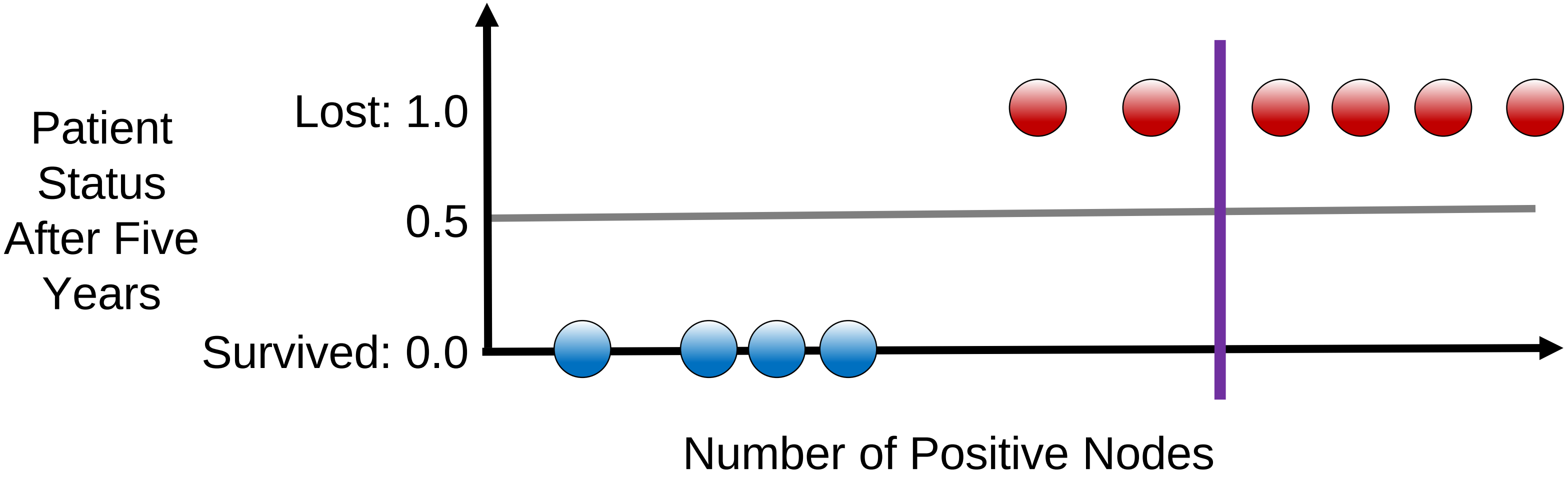


Support Vector Machines (SVM)



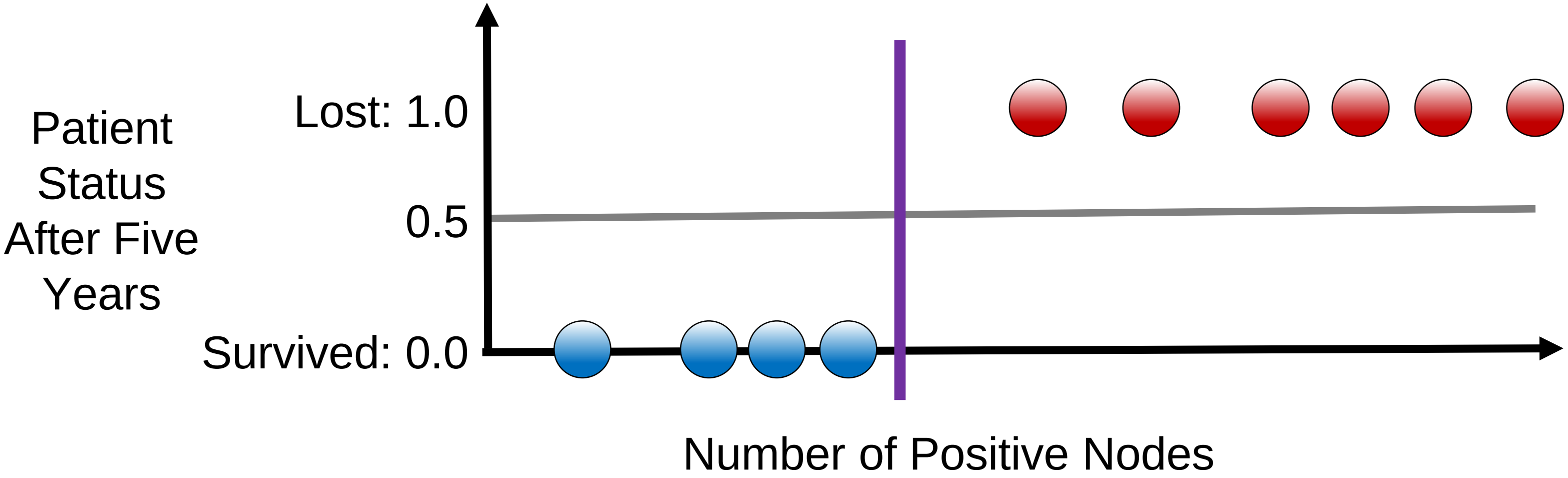
Three misclassifications

Support Vector Machines (SVM)



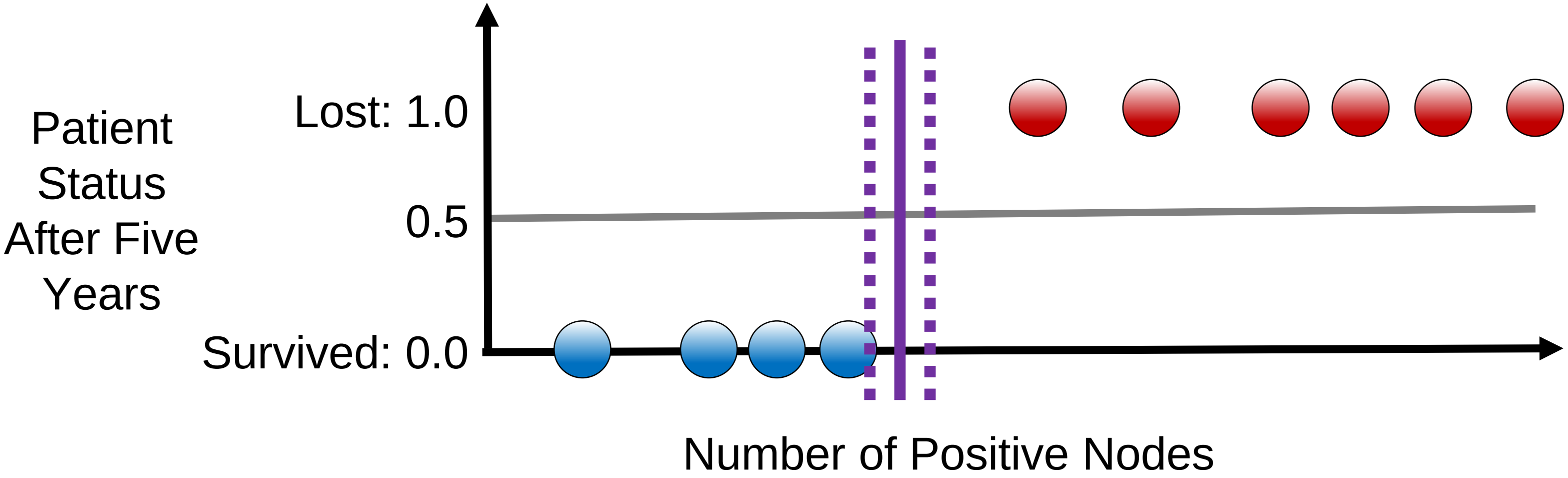
Two misclassifications

Support Vector Machines (SVM)



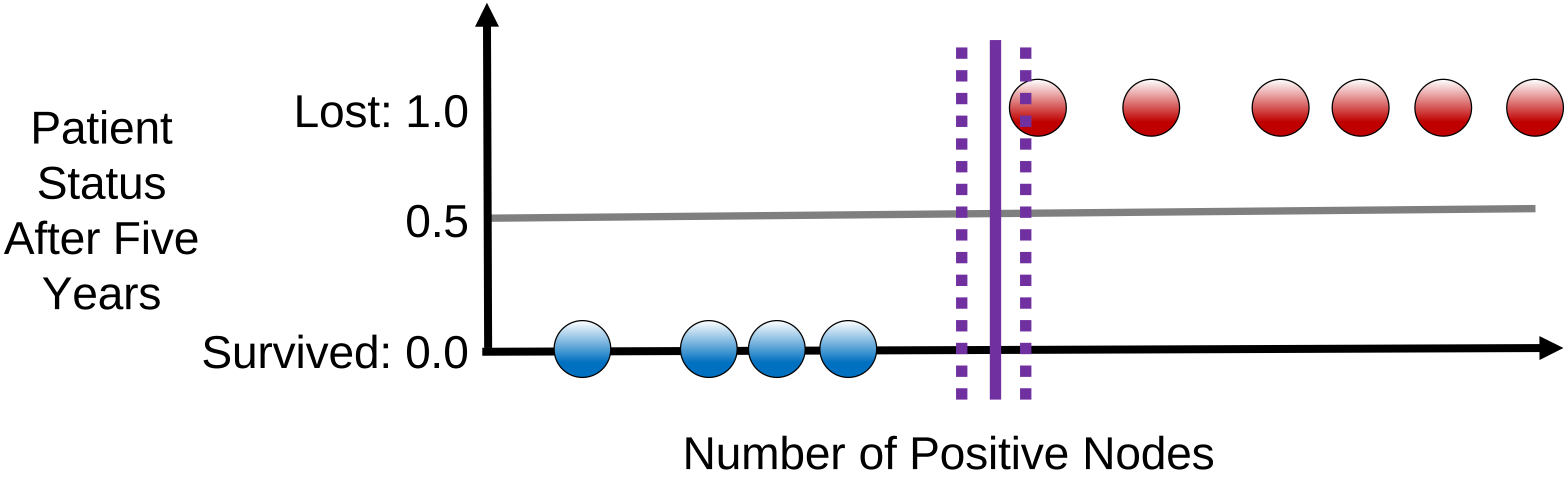
No misclassifications

Support Vector Machines (SVM)



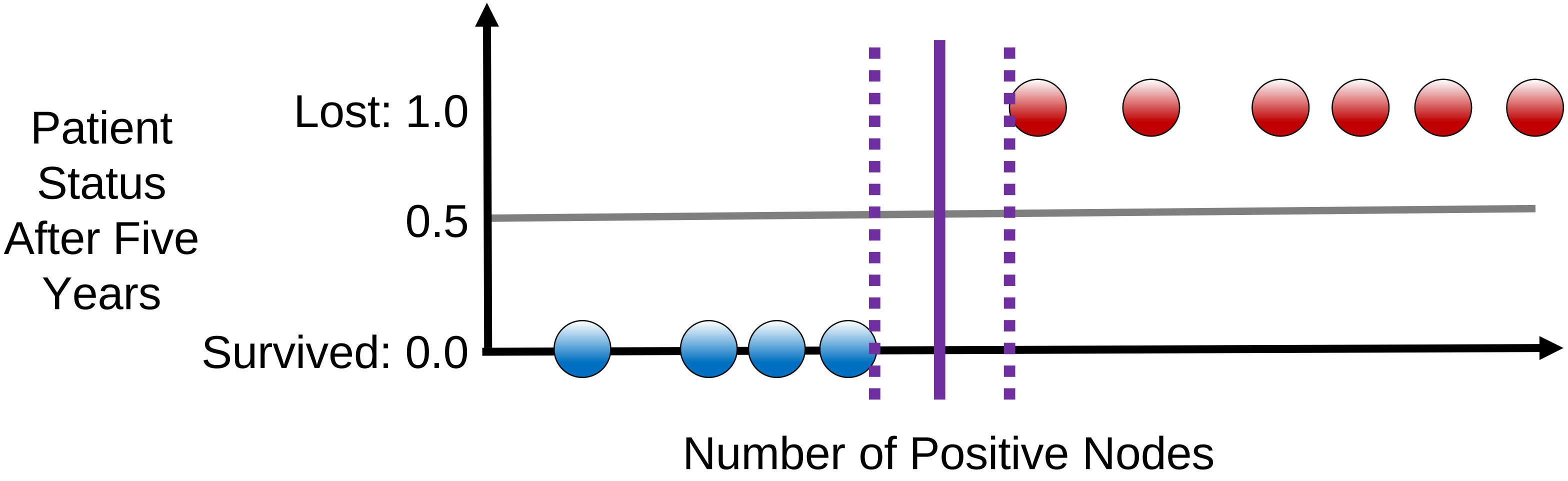
No misclassifications—but is this the best position?

Support Vector Machines (SVM)



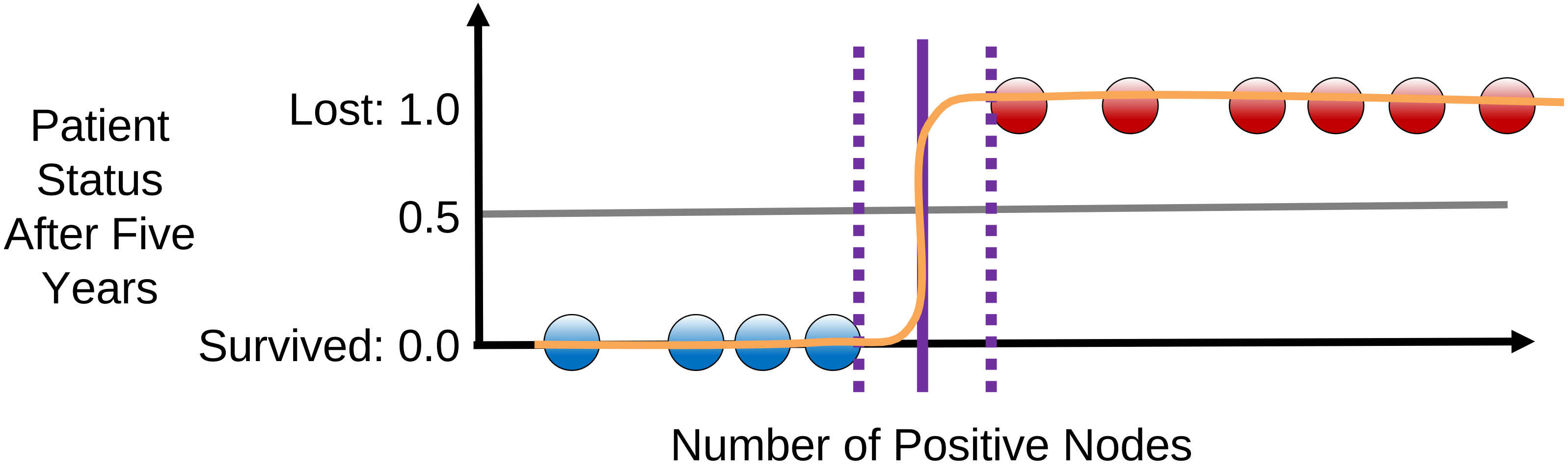
No misclassifications—but is this the best position?

Support Vector Machines (SVM)



Maximize the region between classes

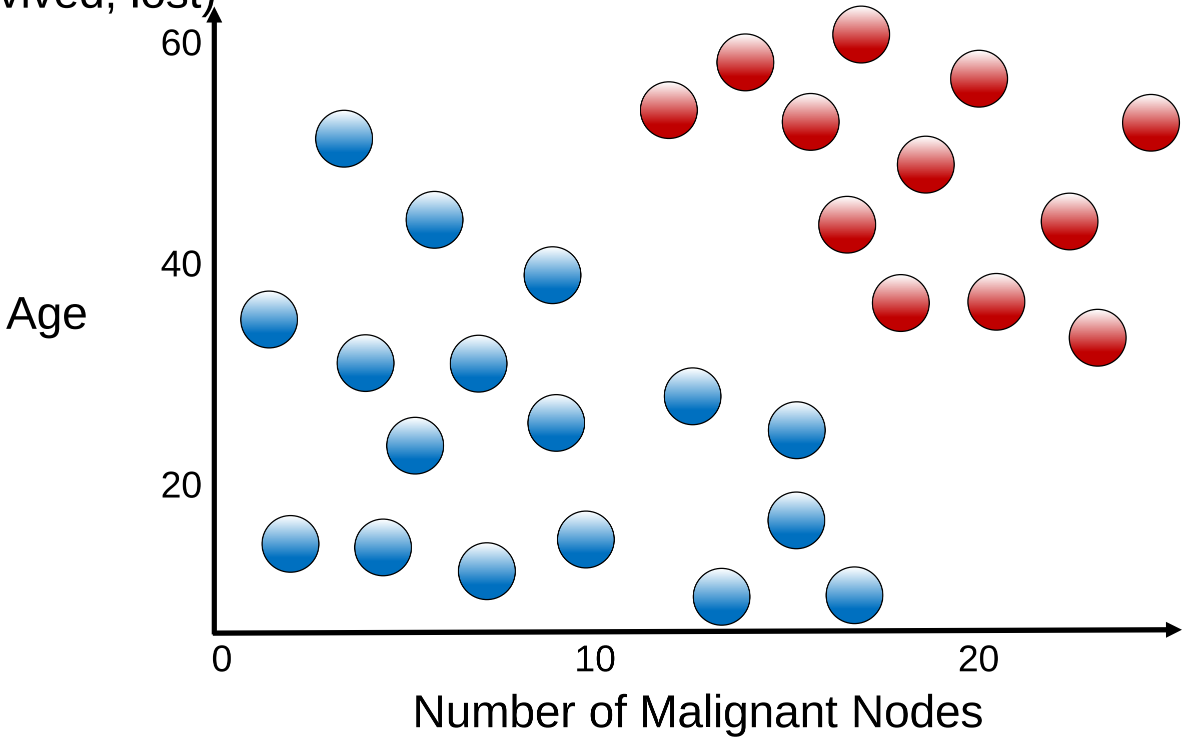
Similarity Between Logistic Regression and SVM



Classification with SVMs

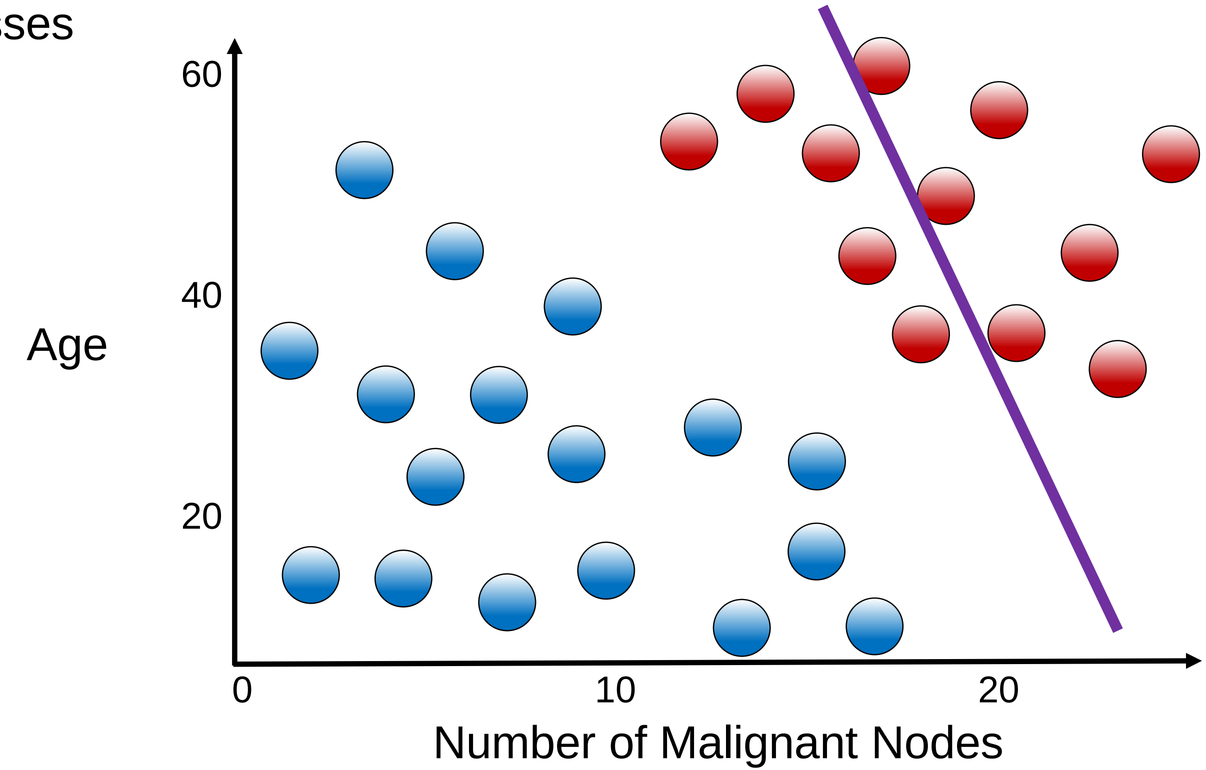
Two features (nodes, age)

Two labels (survived, lost)



Classification with SVMs

Find the line that best separates classes



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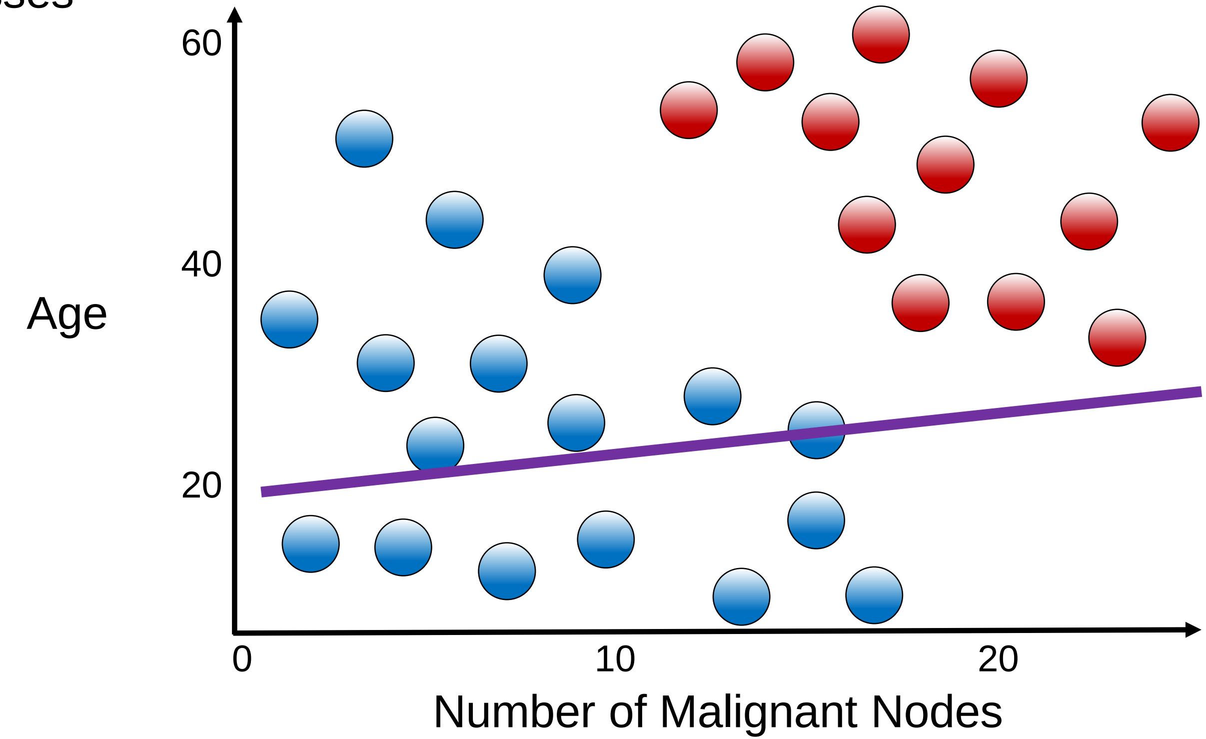

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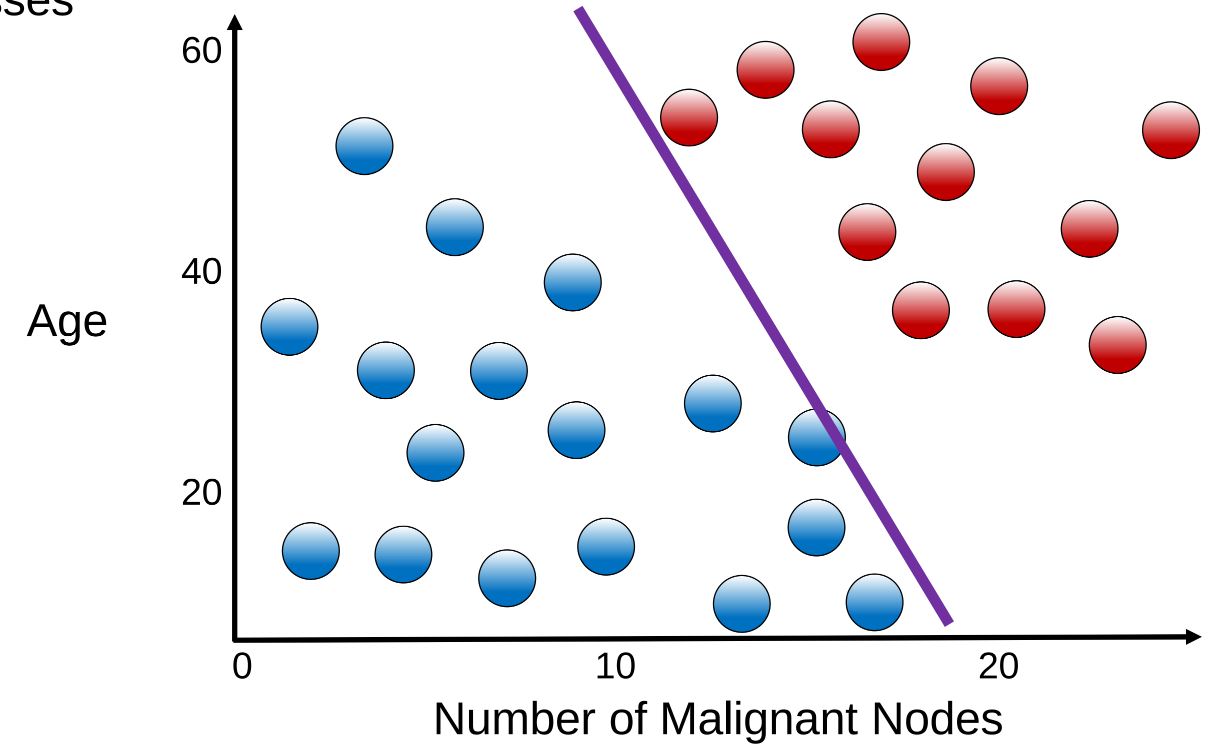
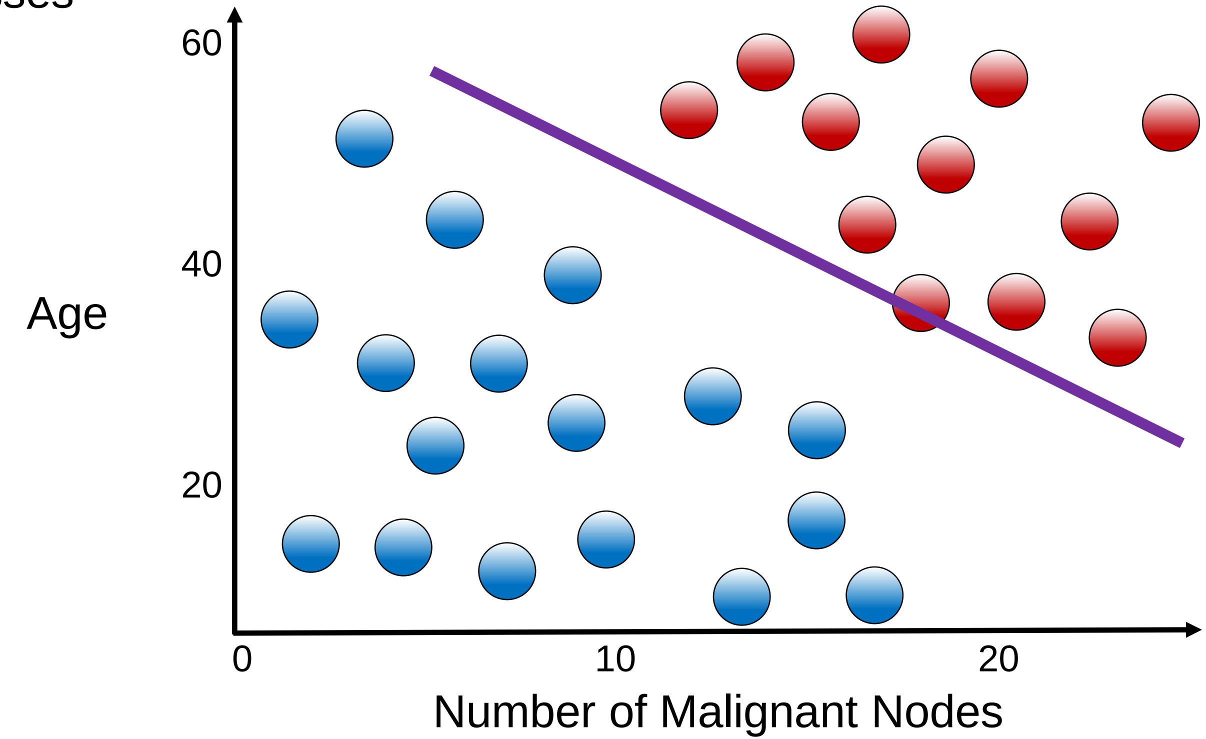


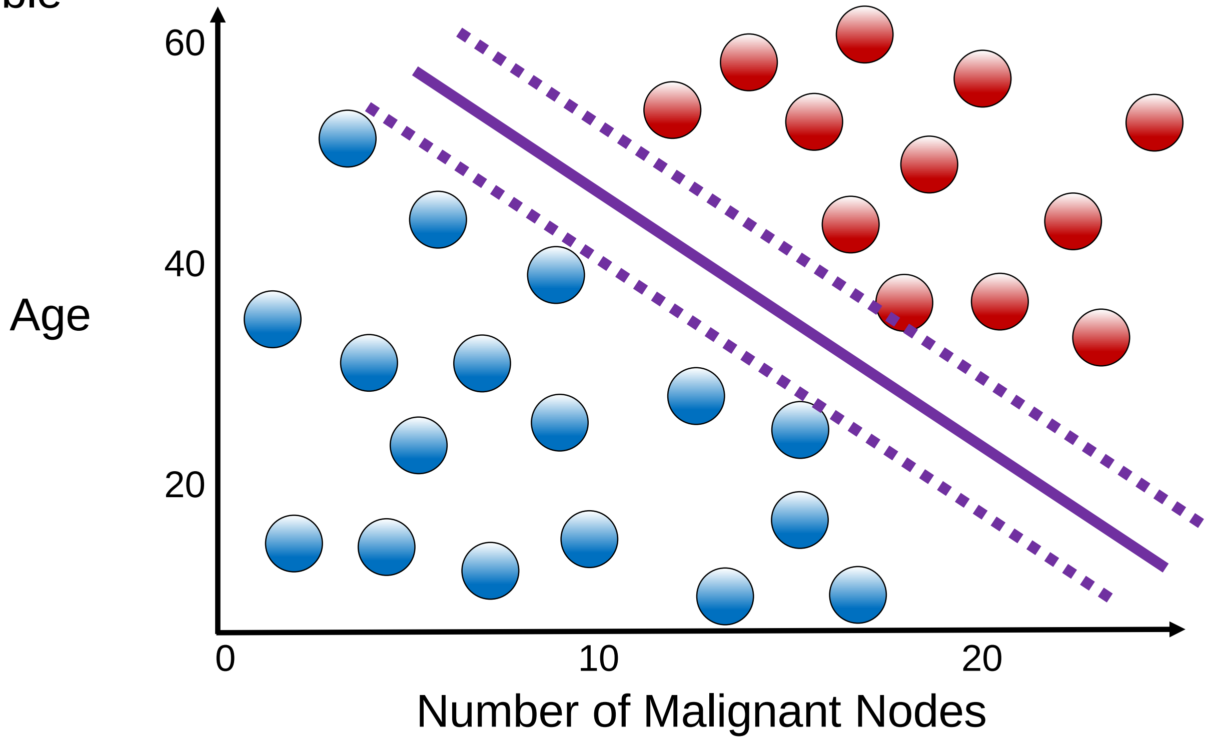
Classification with SVMs

Find the line that best separates classes

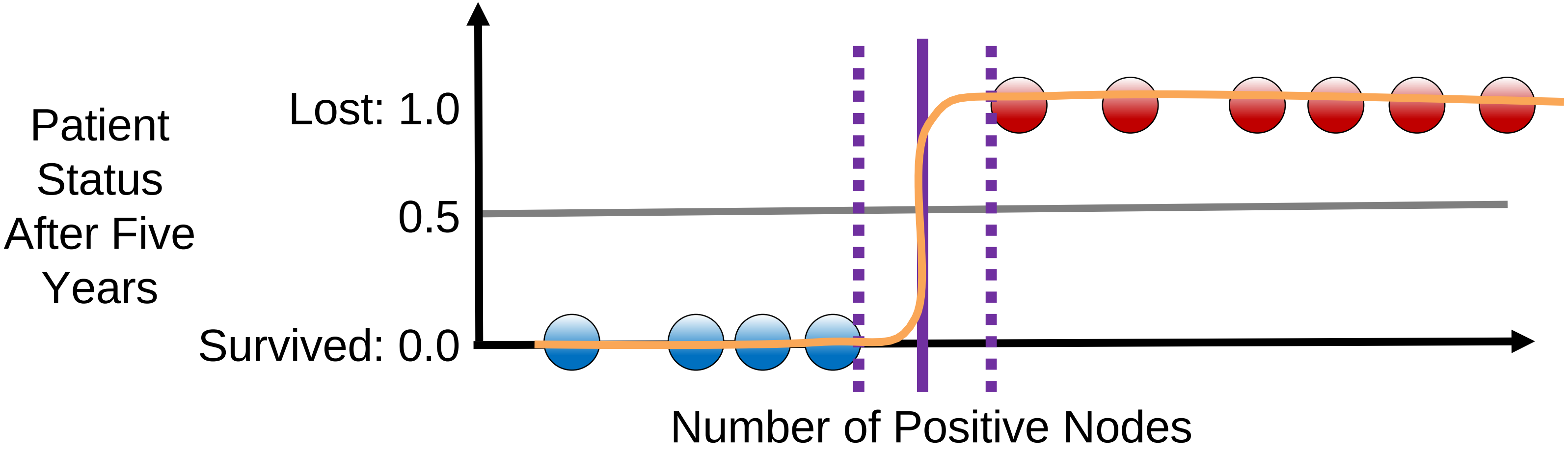


Classification with SVMs

And include the largest boundary possible



Logistic Regression vs SVM Cost Functions



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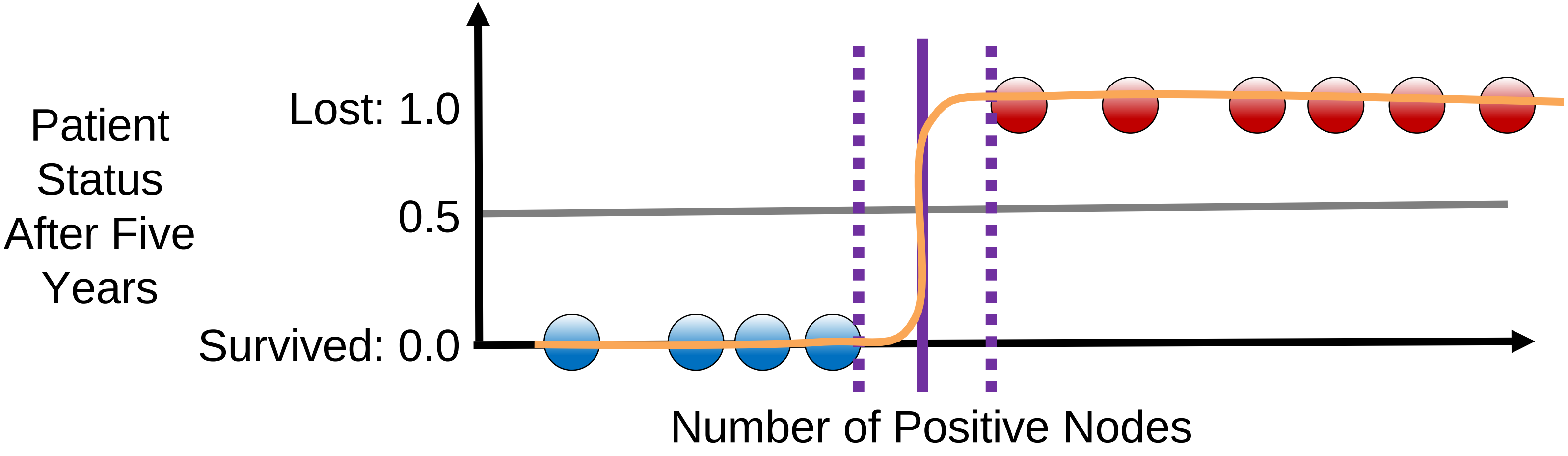

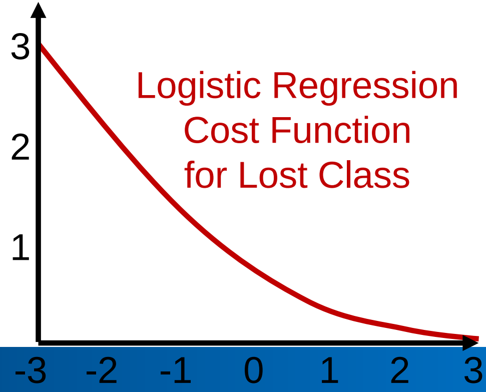

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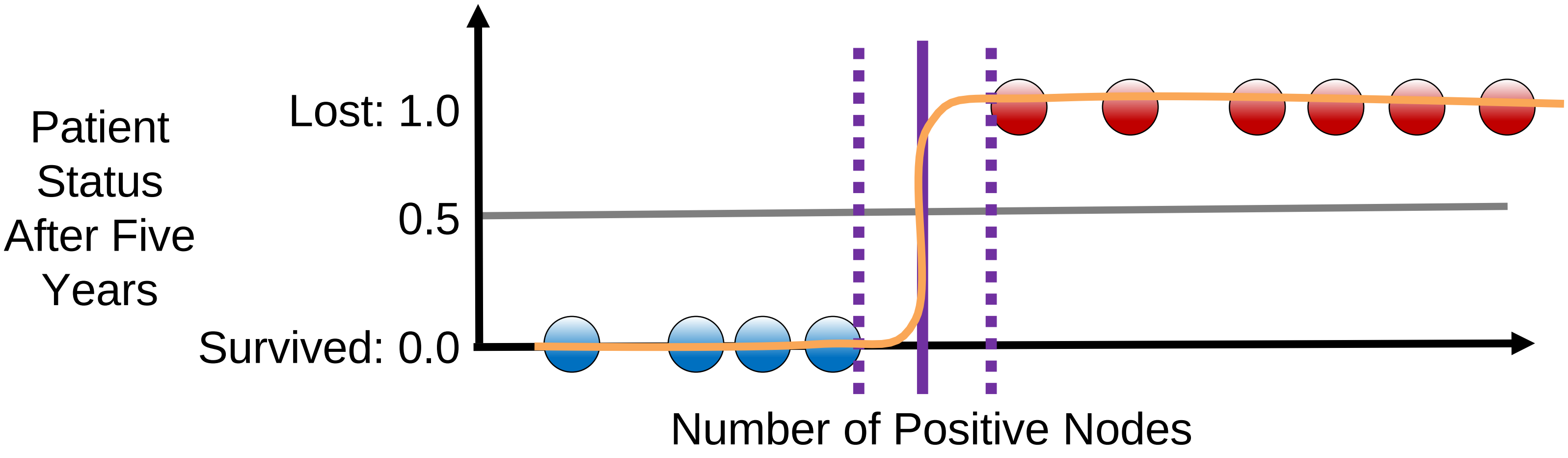
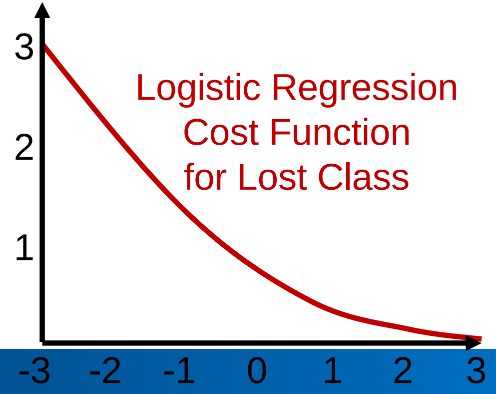
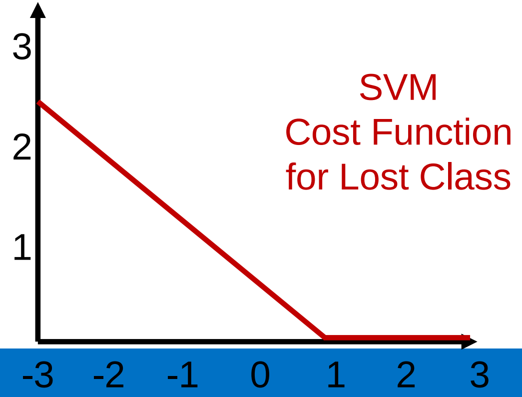
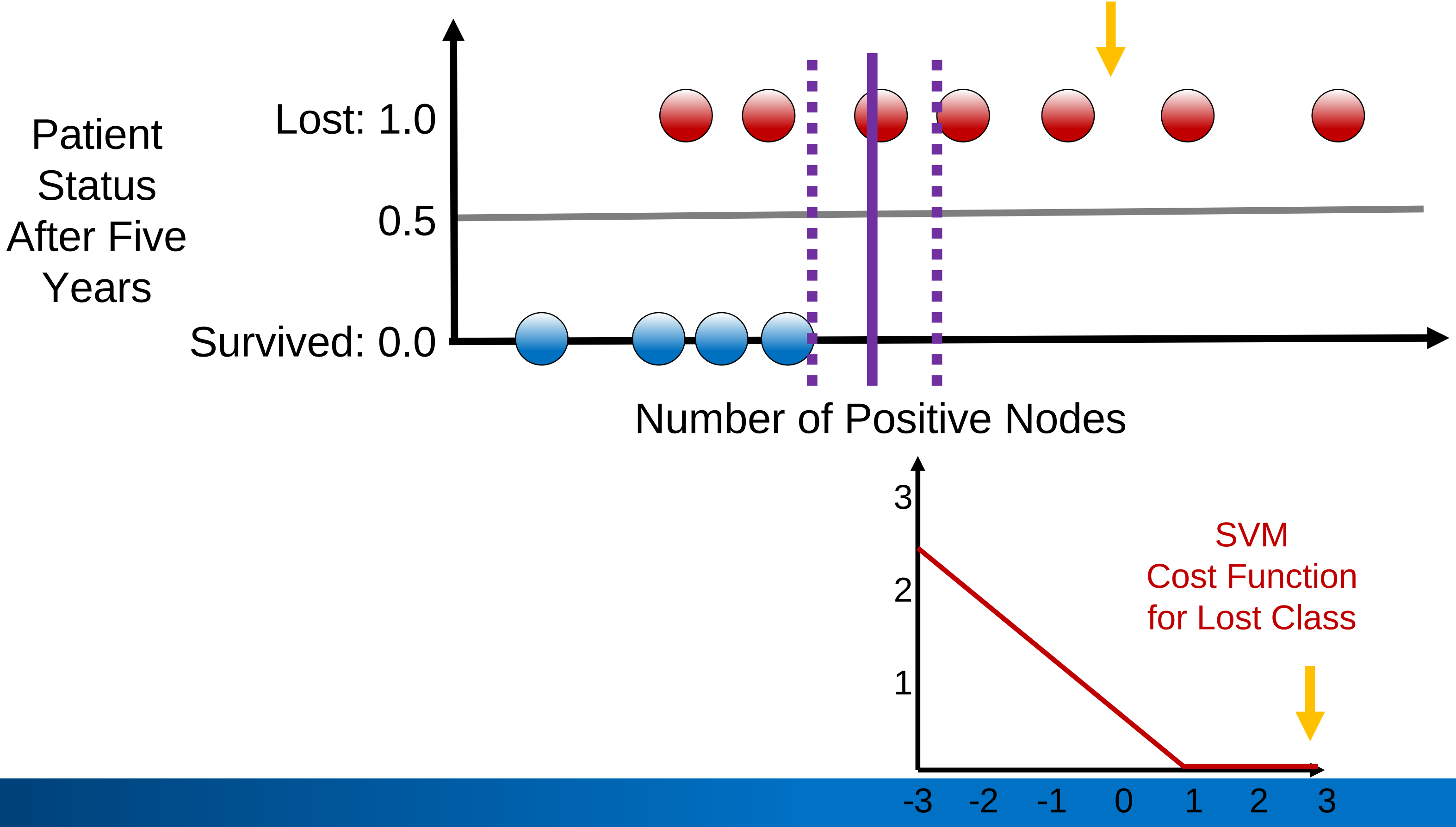






The SVM Cost Function



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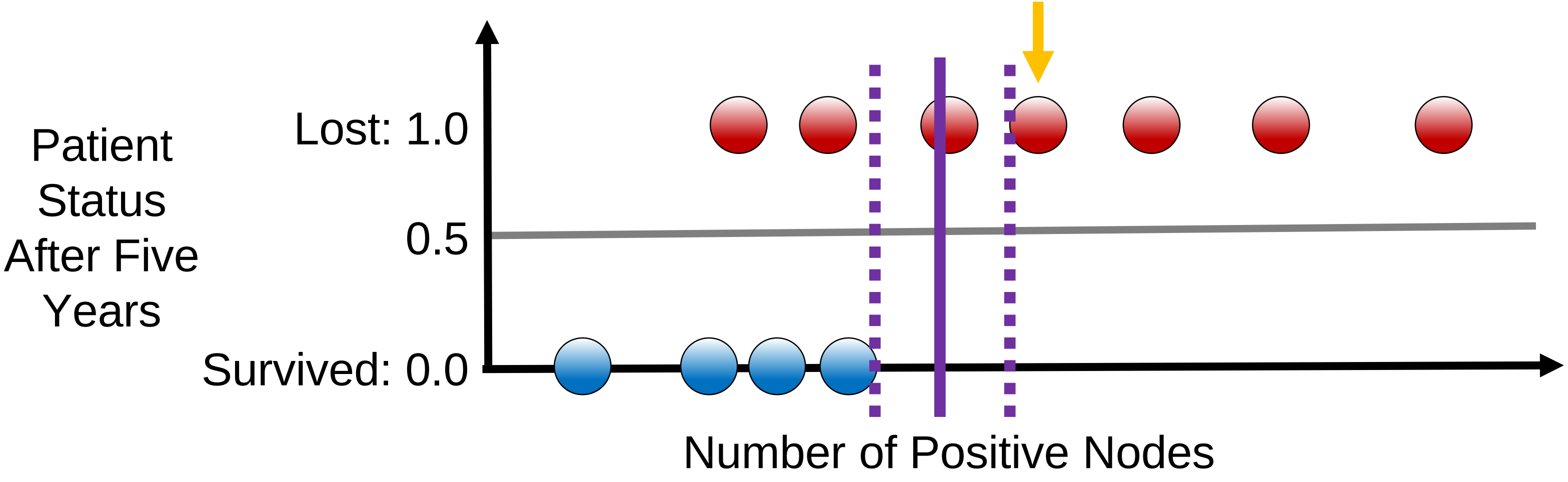

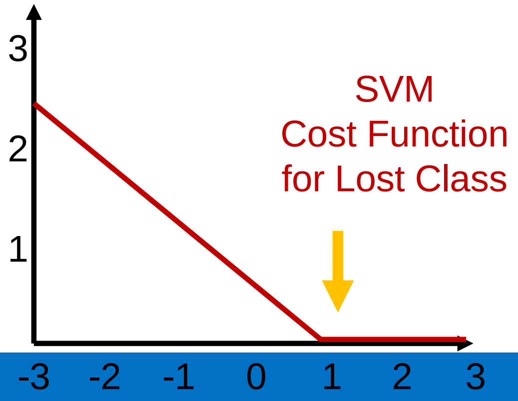

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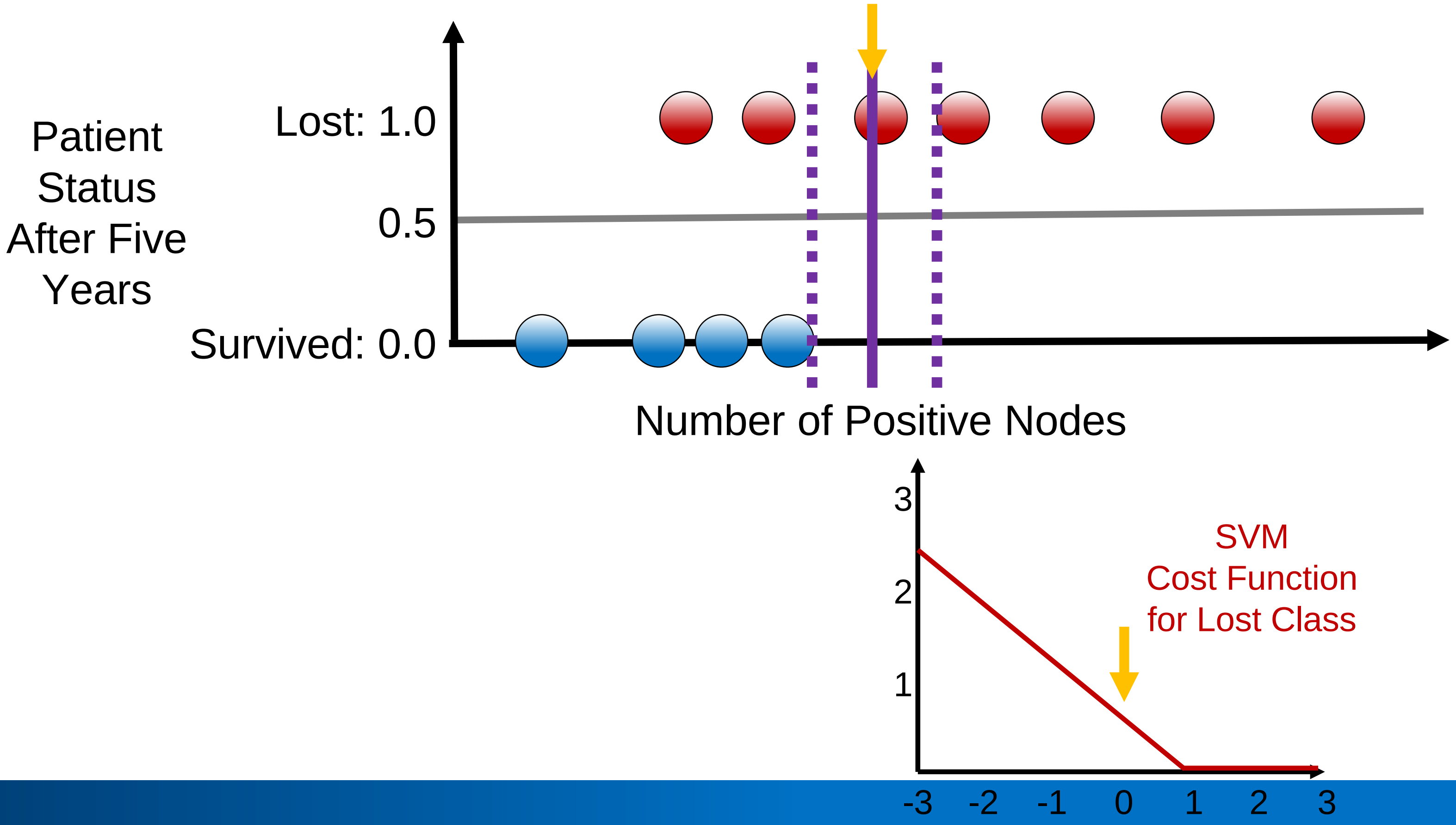

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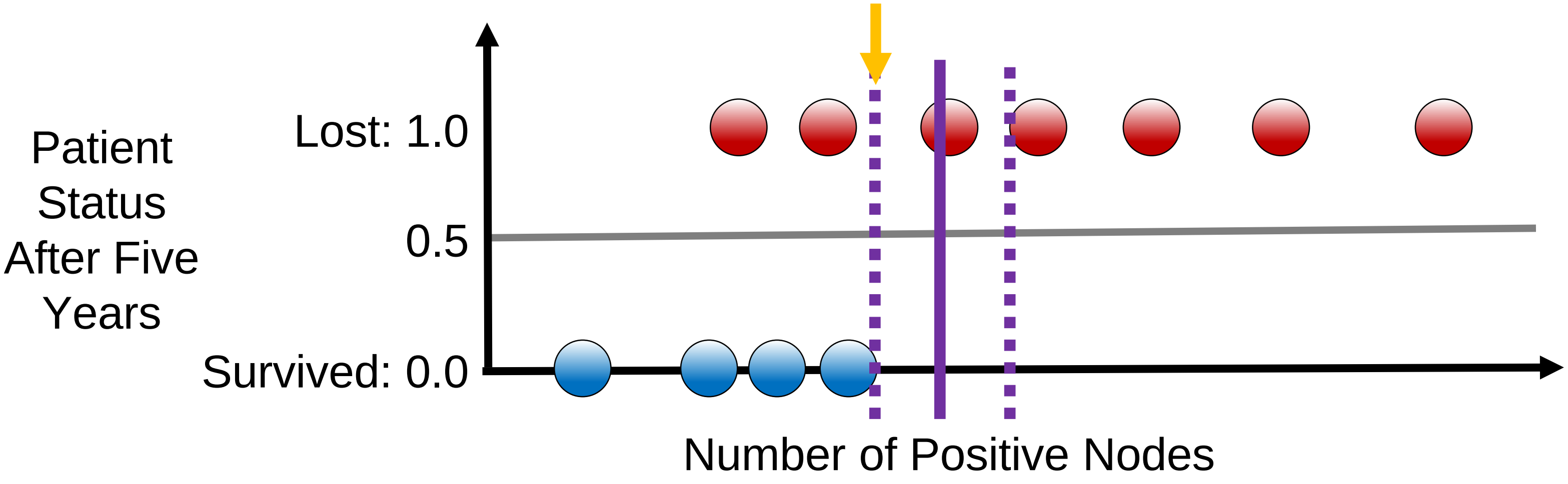

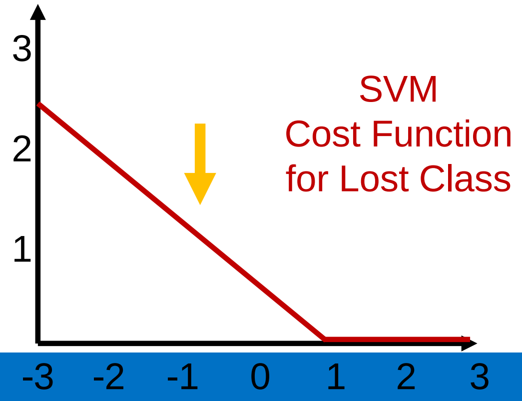

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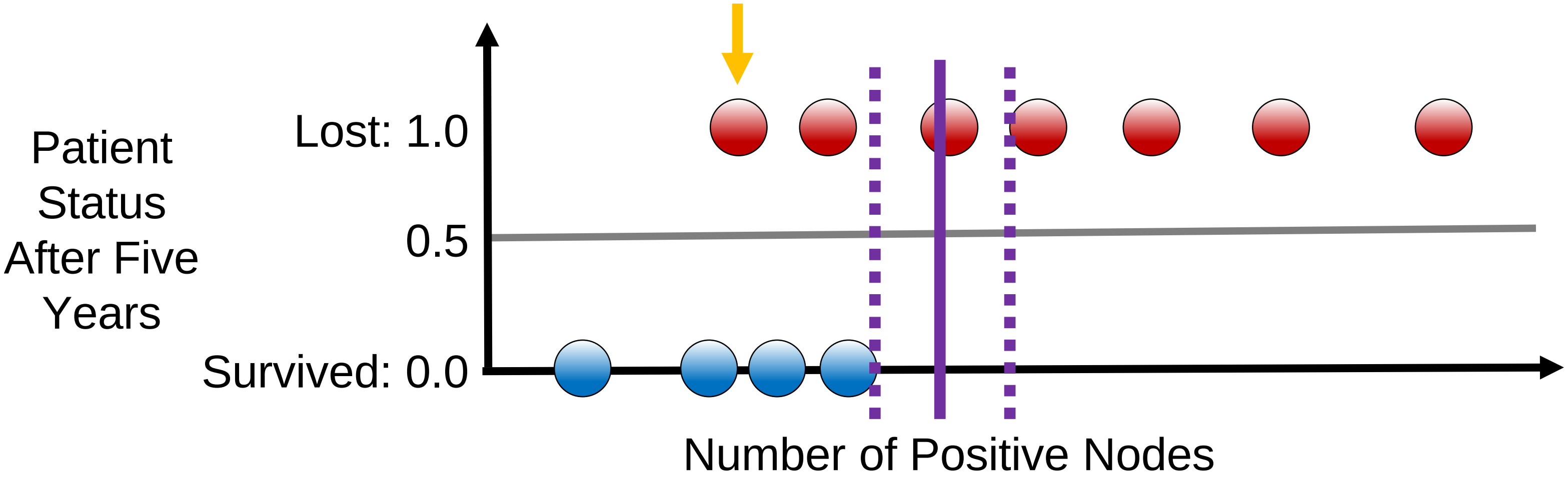
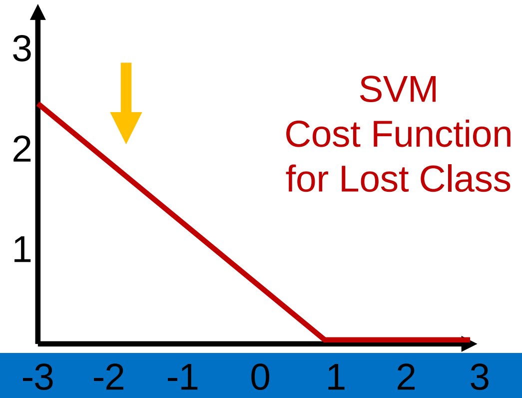
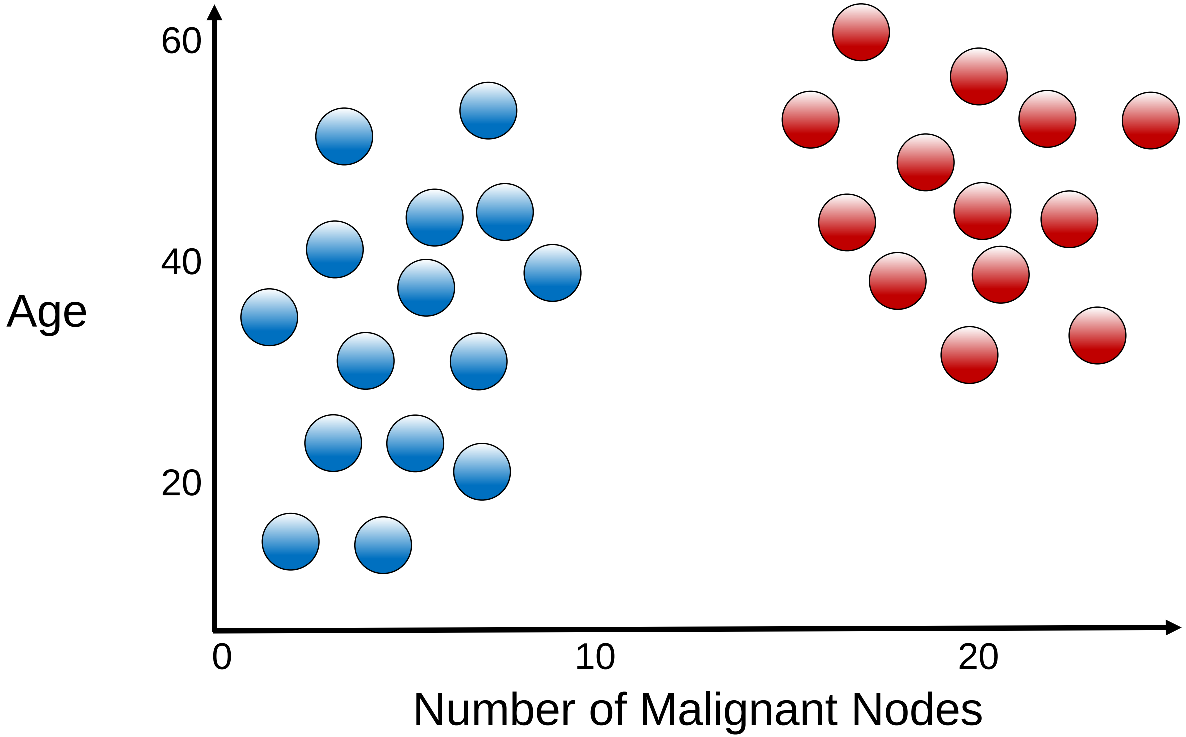




Outlier Sensitivity in SVMs



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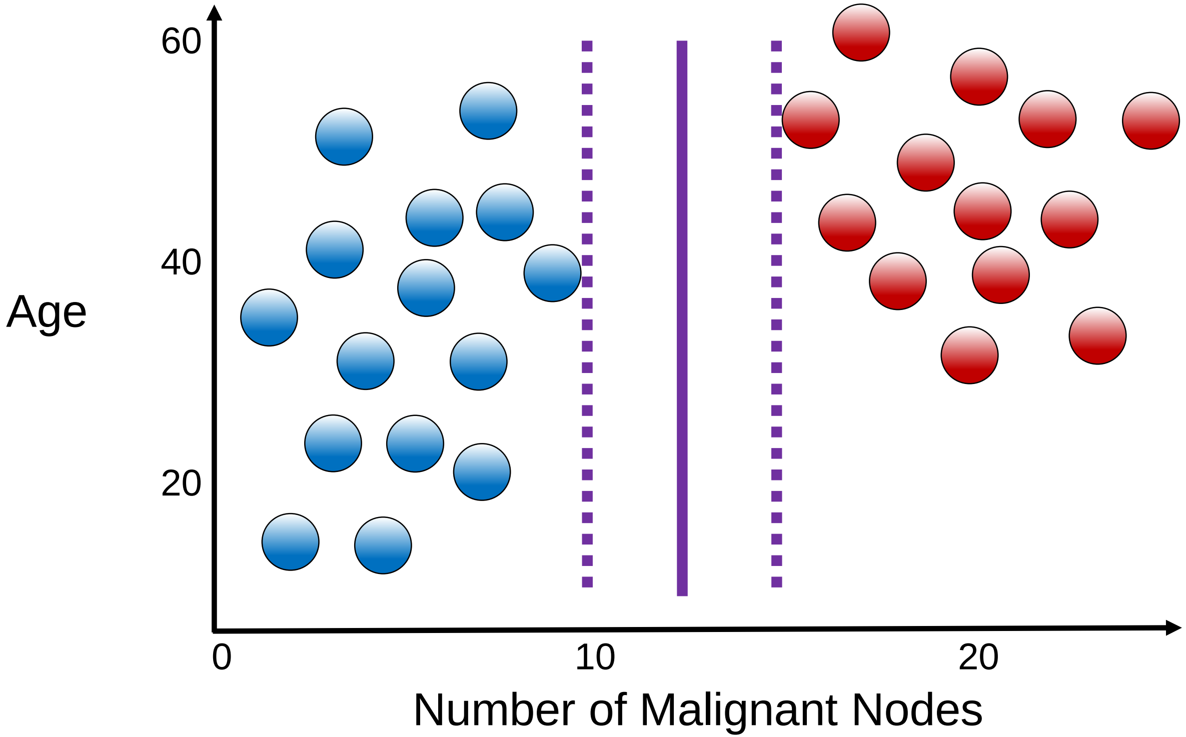

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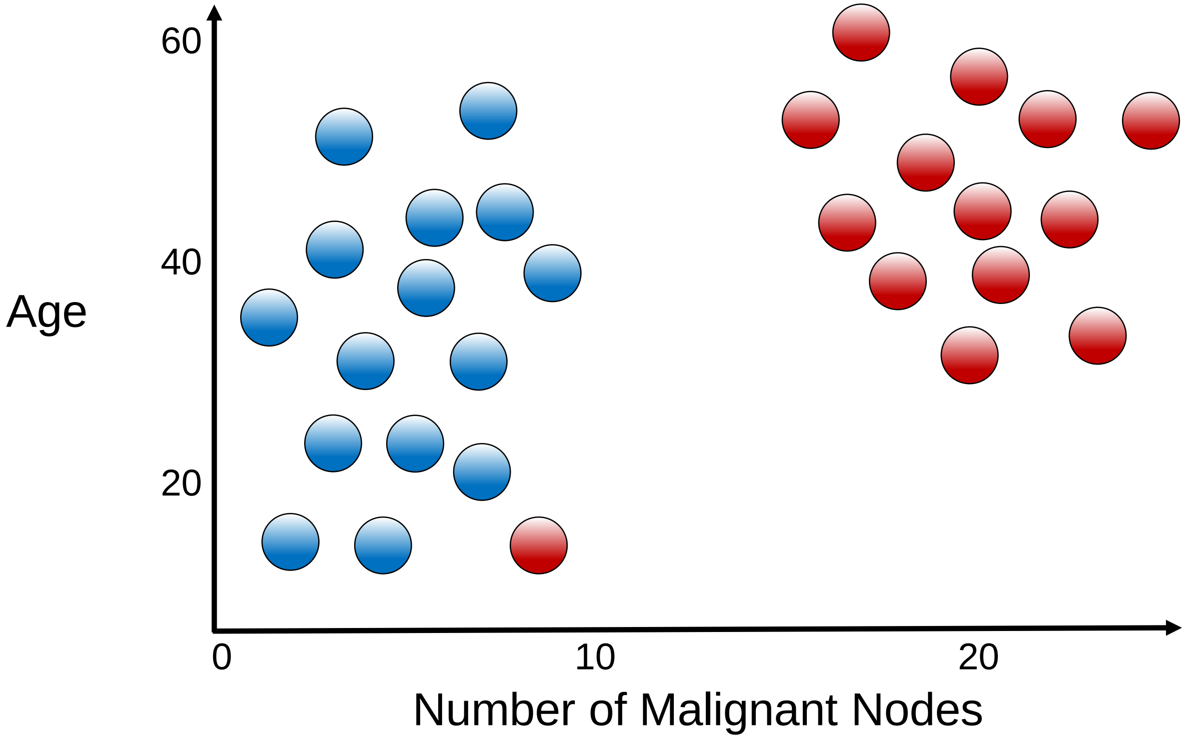

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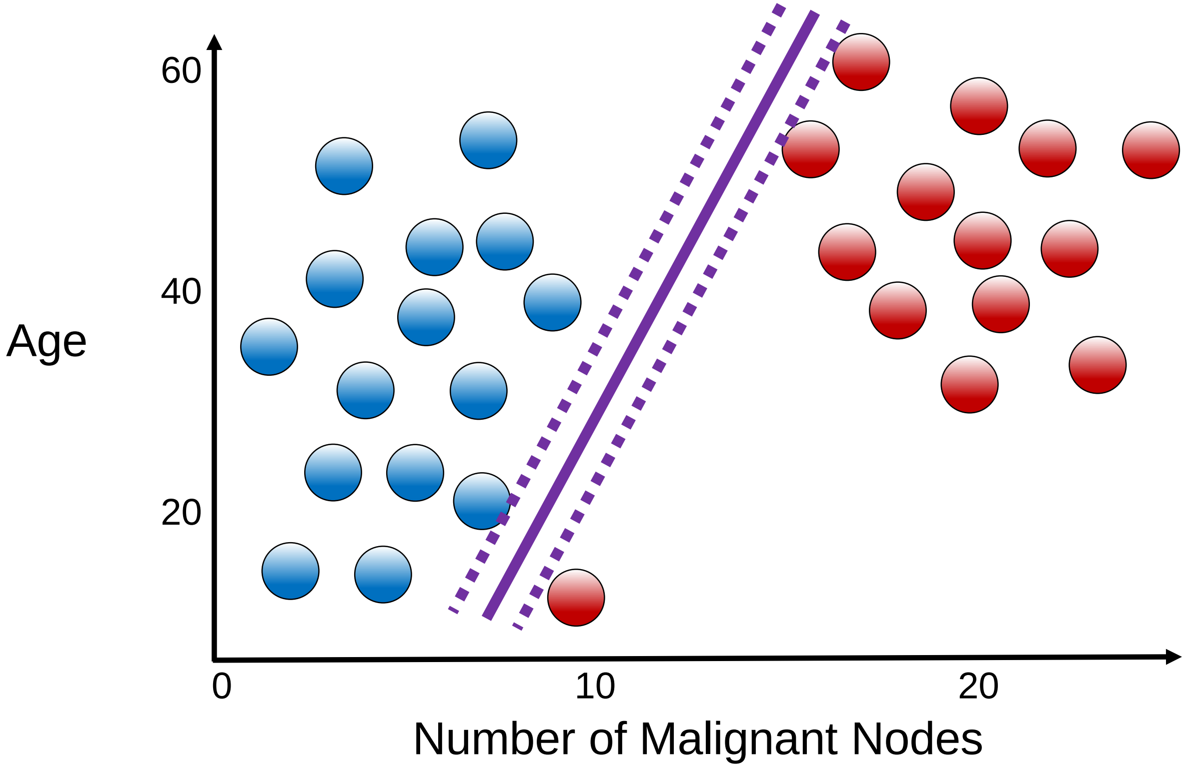
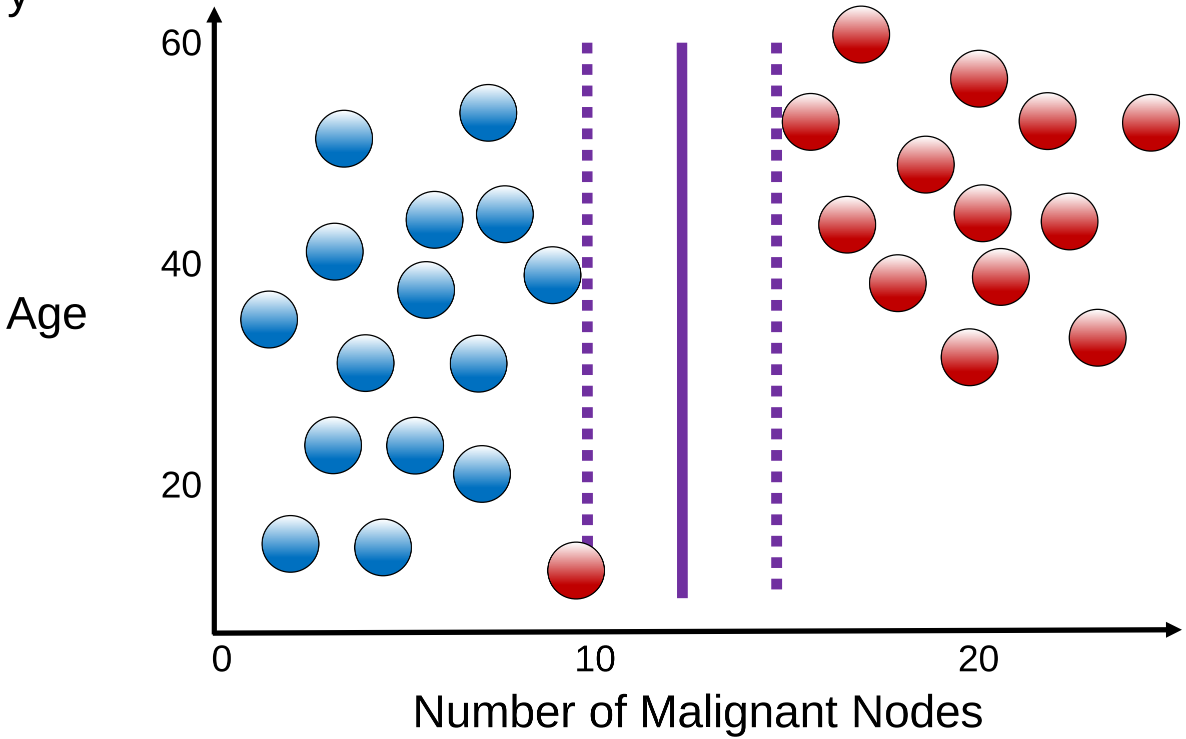


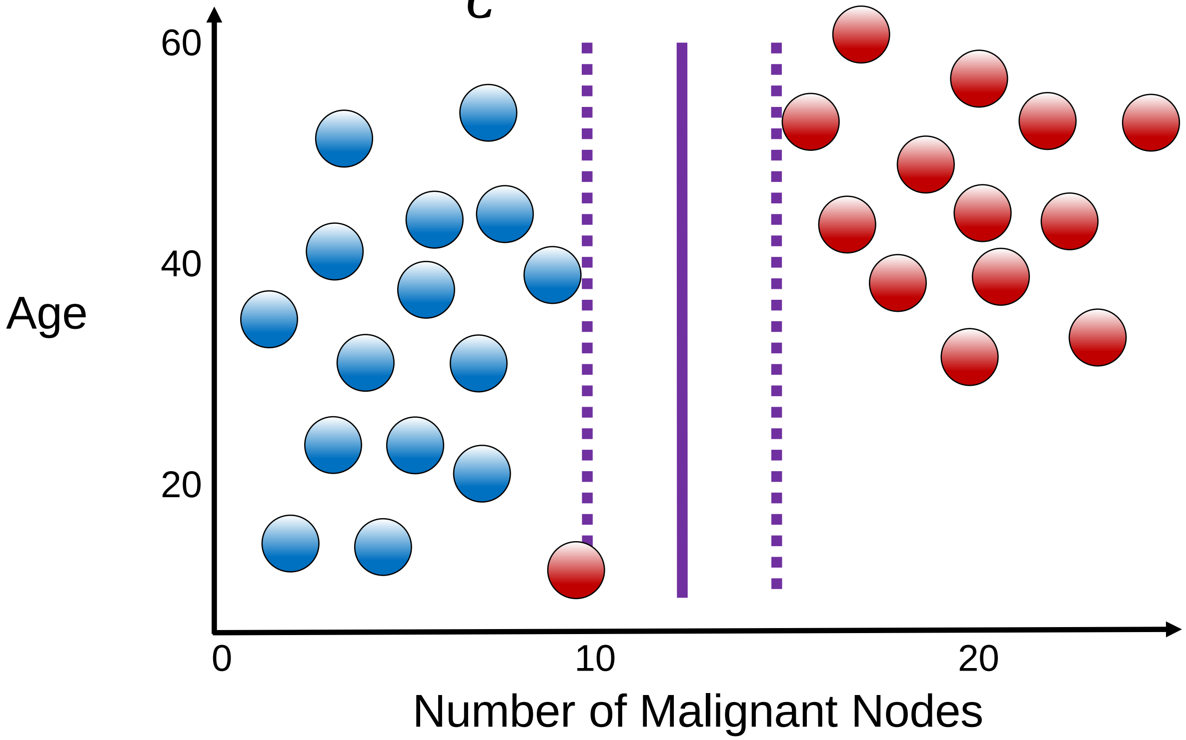
Outlier Sensitivity in SVMs

This is probably still the correct boundary



Regularization in SVMs

$$J(\beta_i) \ = SVMCost(\beta_i) + \frac{1}{C}\sum_i \beta_i$$



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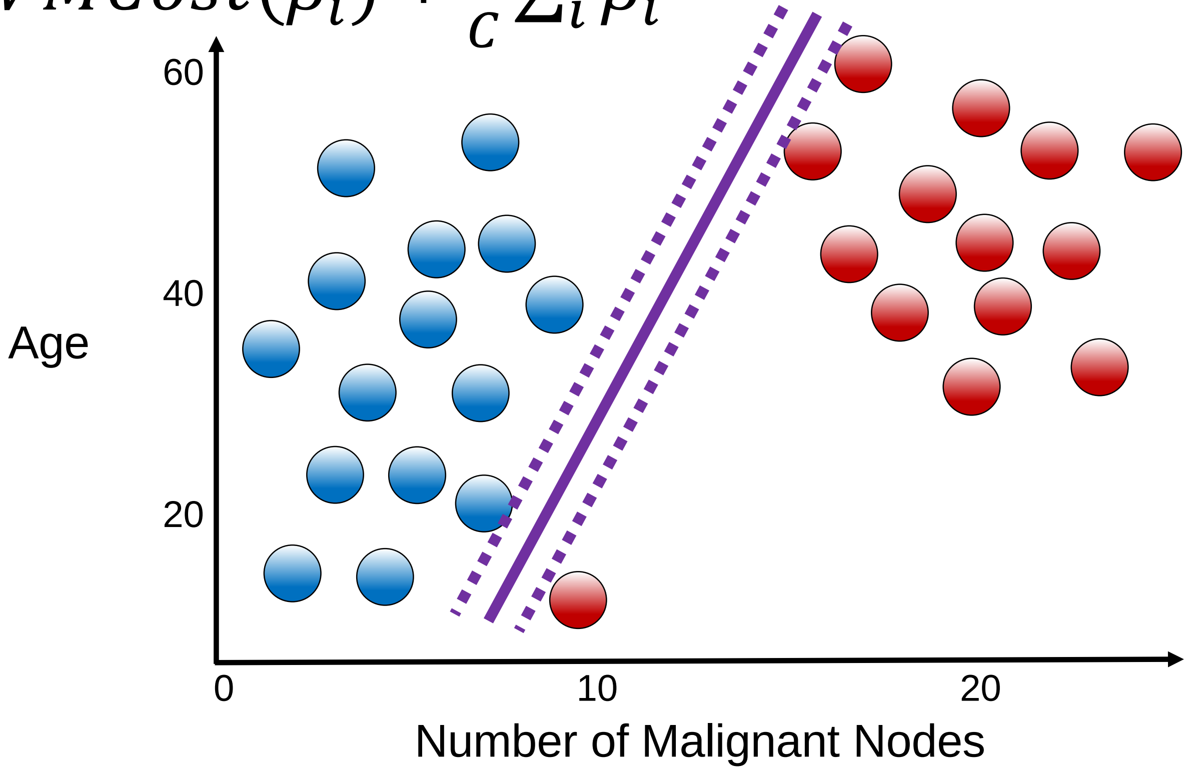

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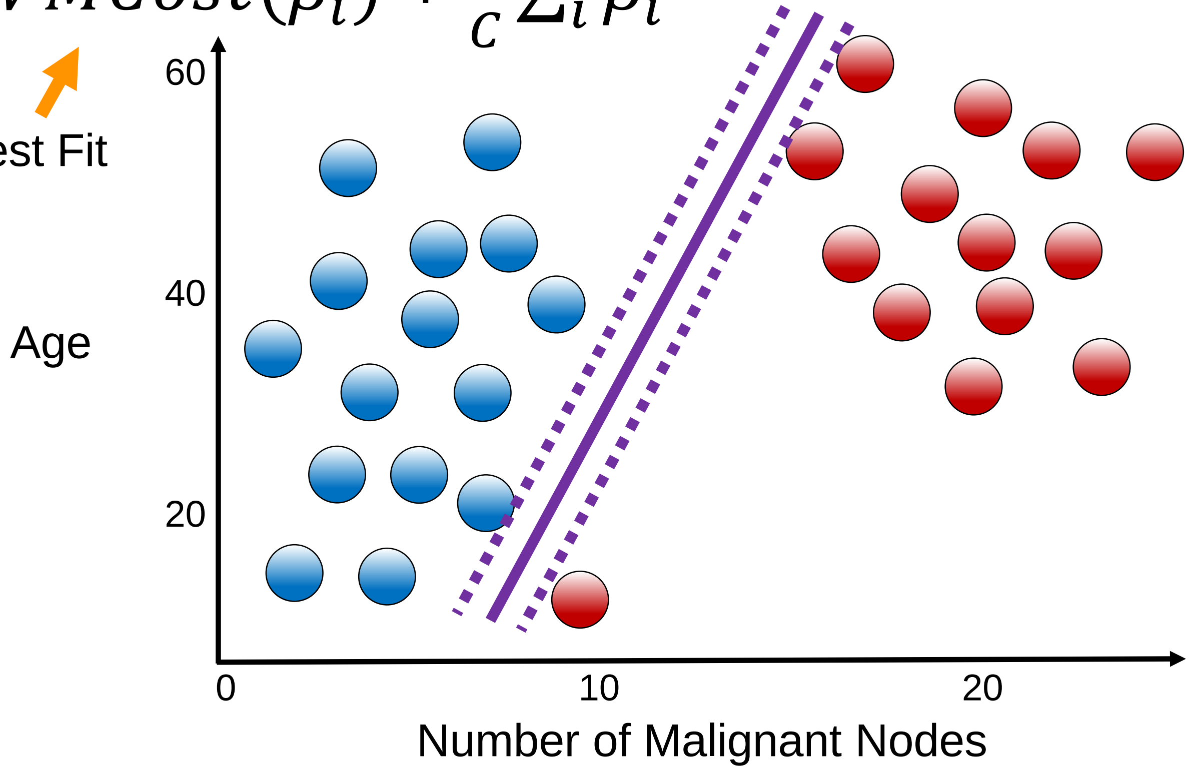
Best Fit



Regularization in SVMs

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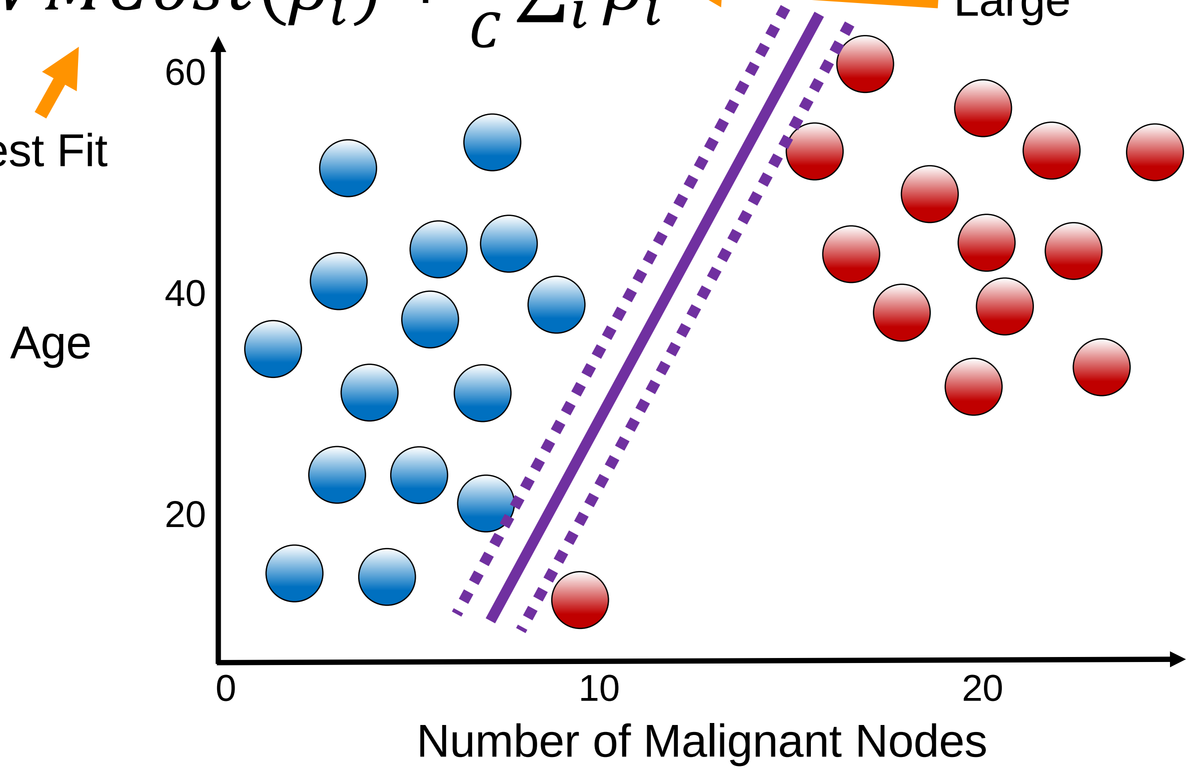
Large

Best Fit



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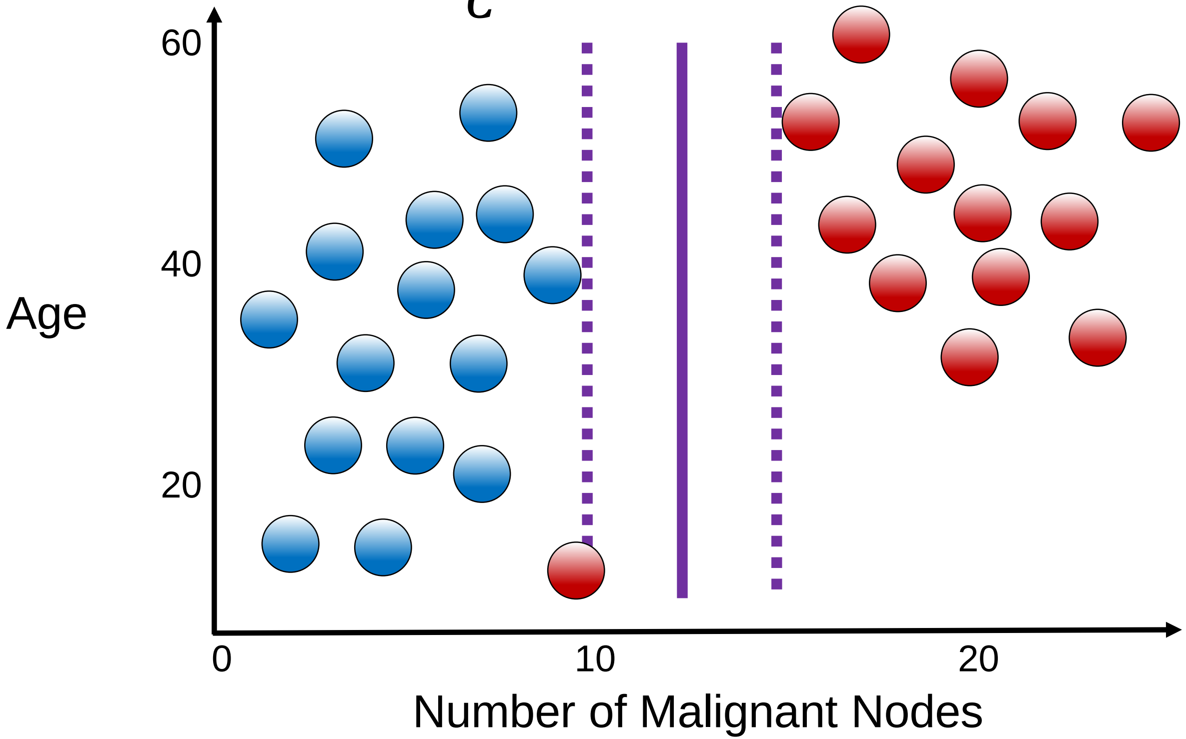

Regularization in SVMs

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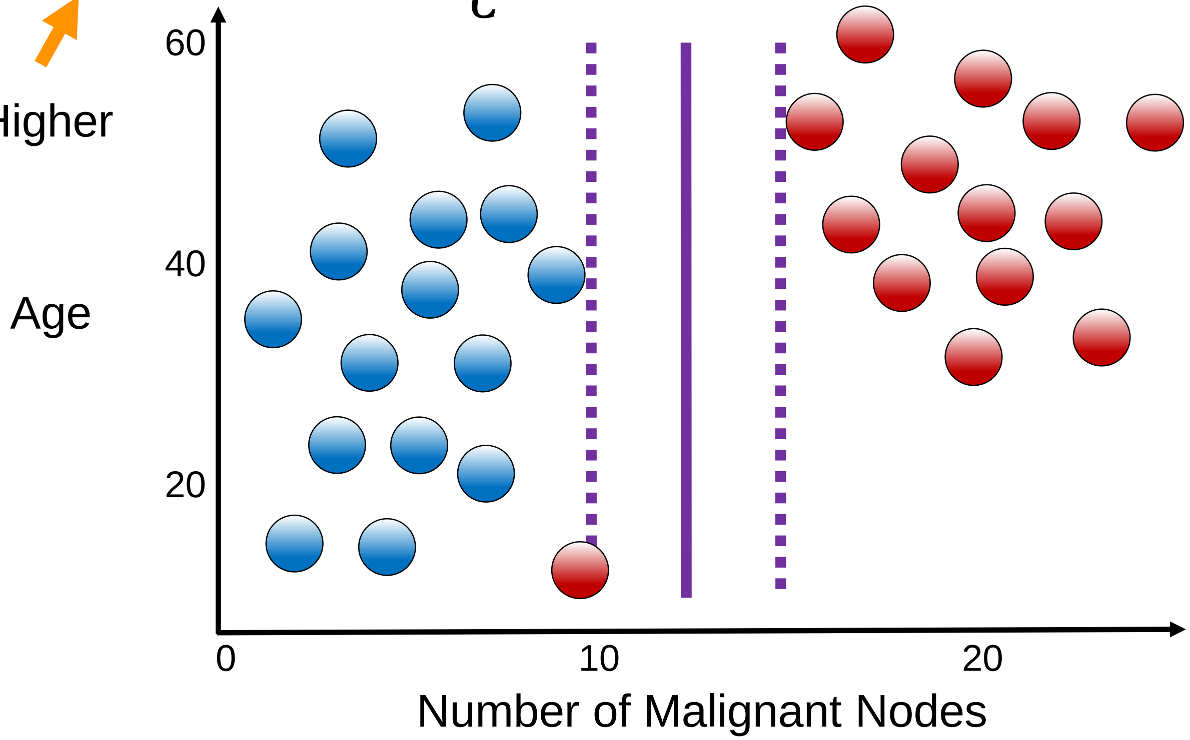
Slightly Higher



Regularization in SVMs

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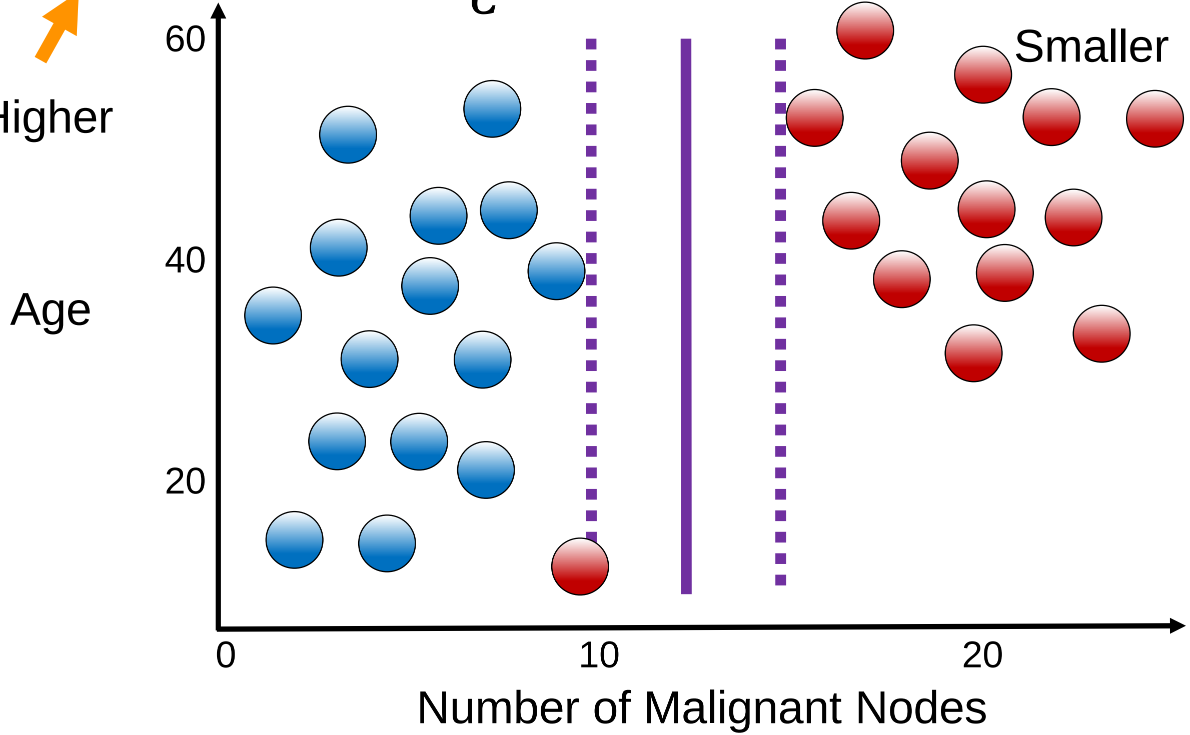
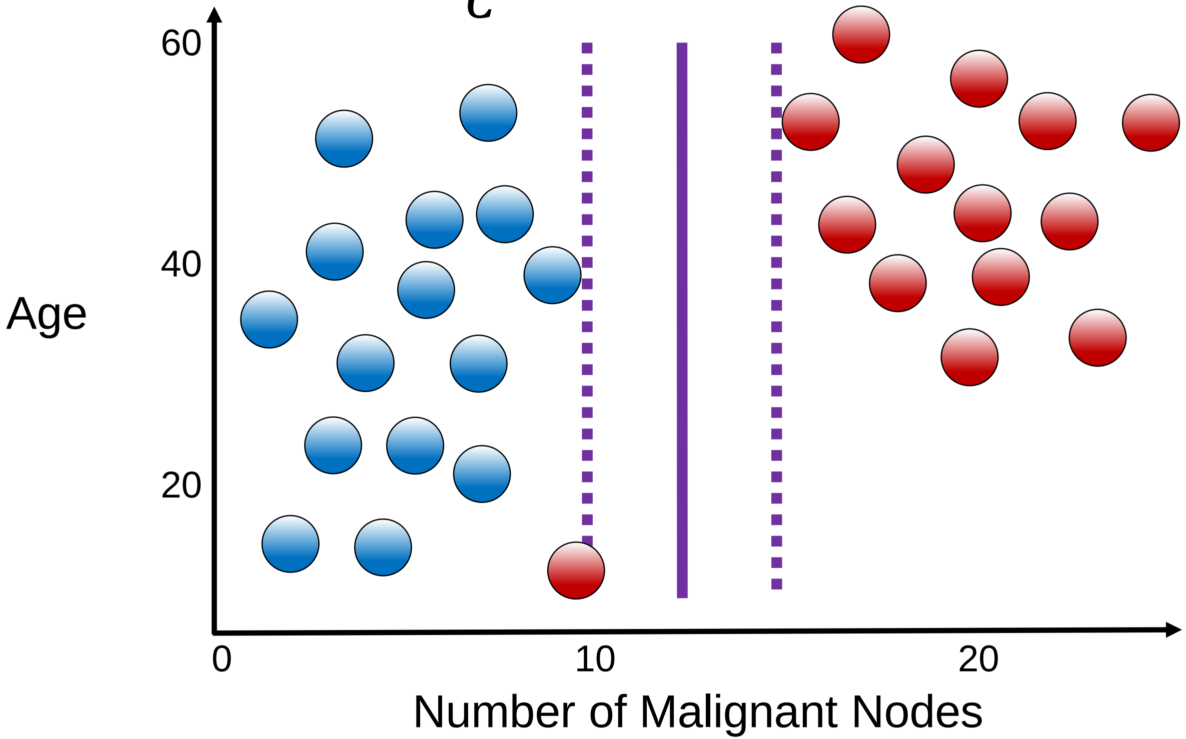
Slightly Higher

Much Smaller



Interpretation of SVM Coefficients

$$J(\beta_i) = SVMCost(\beta_i) + \frac{1}{C}\sum_i \beta_i$$



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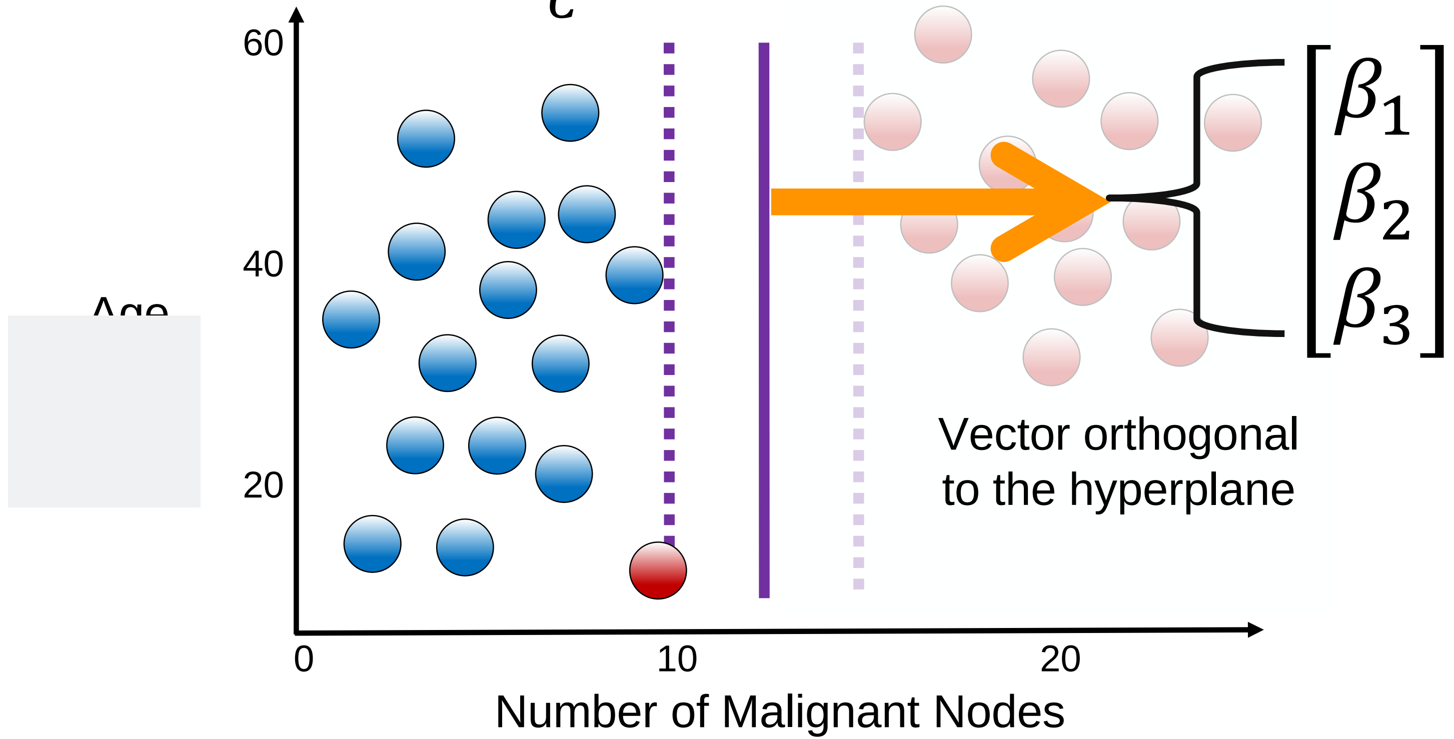

Linear SVM: The Syntax

Import the class containing the classification method

```
from sklearn.svm import LinearSVC
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Create an instance of the class

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LinSVC = LinearSVC(penalty='l2', C=10.0)
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regularization parameters

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Fit the instance on the data and then predict the expected value

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LinSVC = LinSVC.fit(X_train, y_train)
y_predict = LinSVC.predict(X_test)
```

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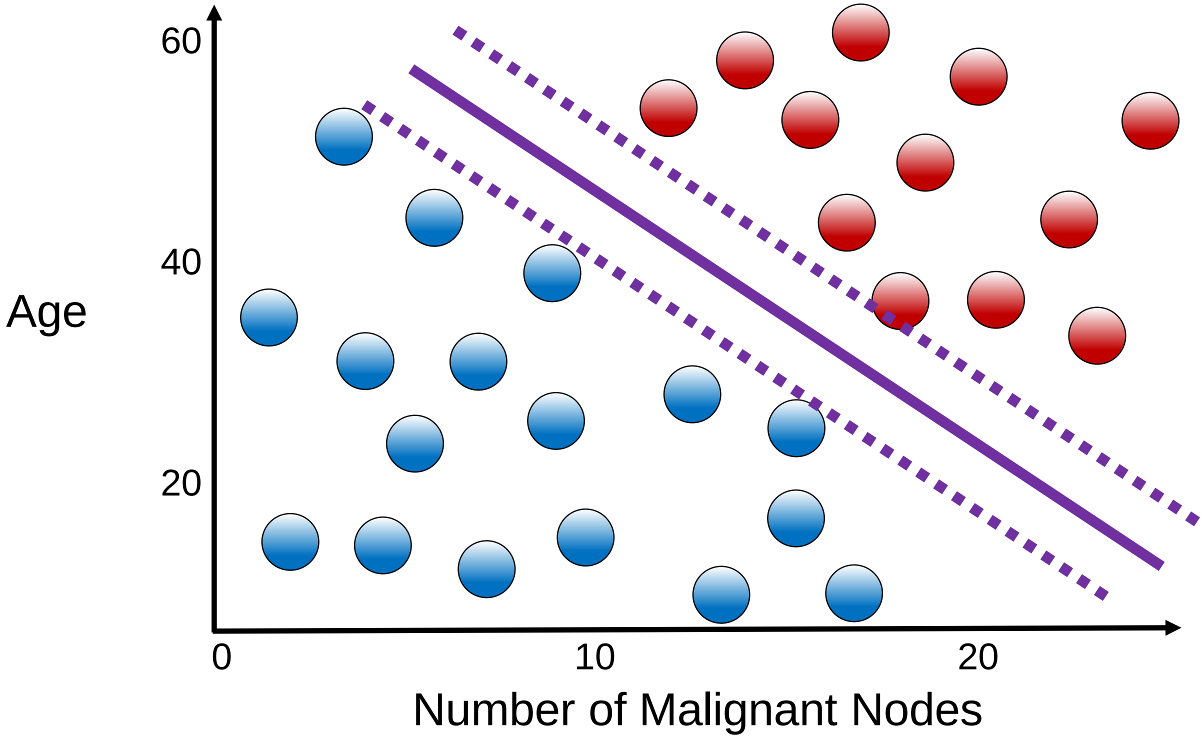
```

Tune regularization parameters with cross-validation.

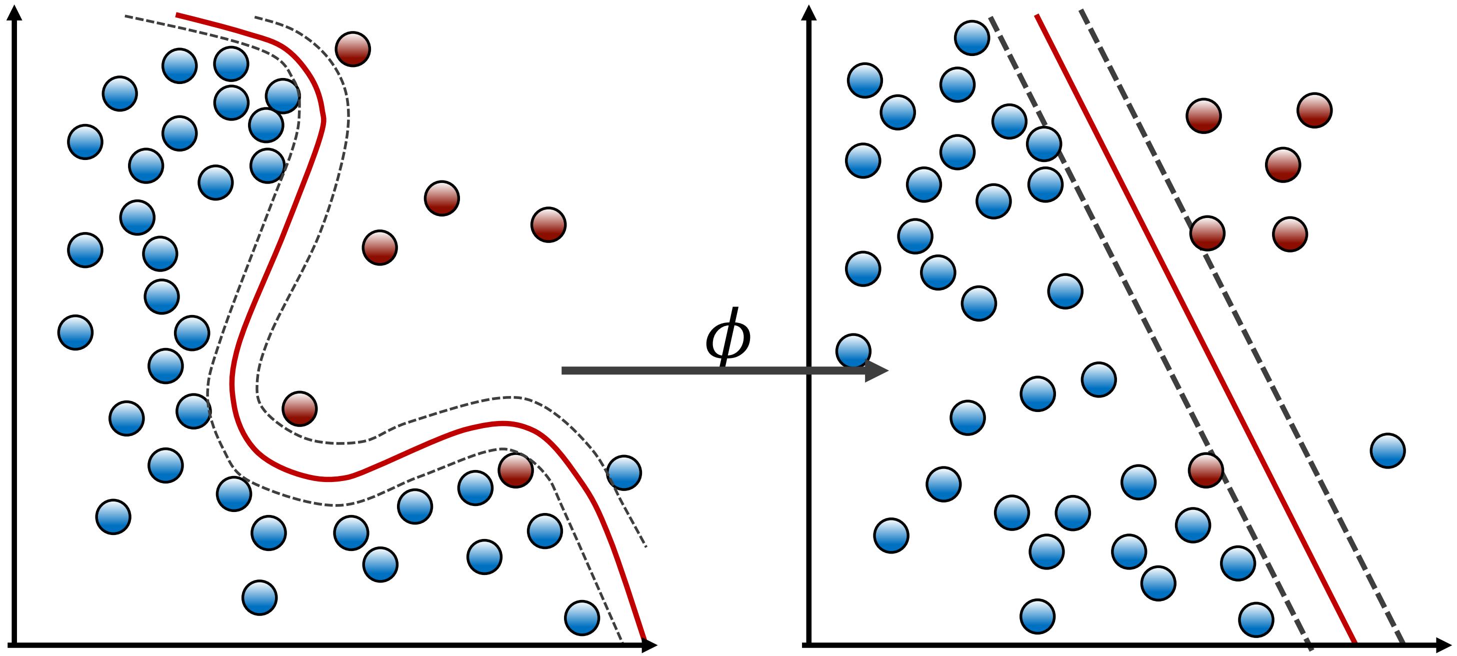
Kernels

Classification with SVMs



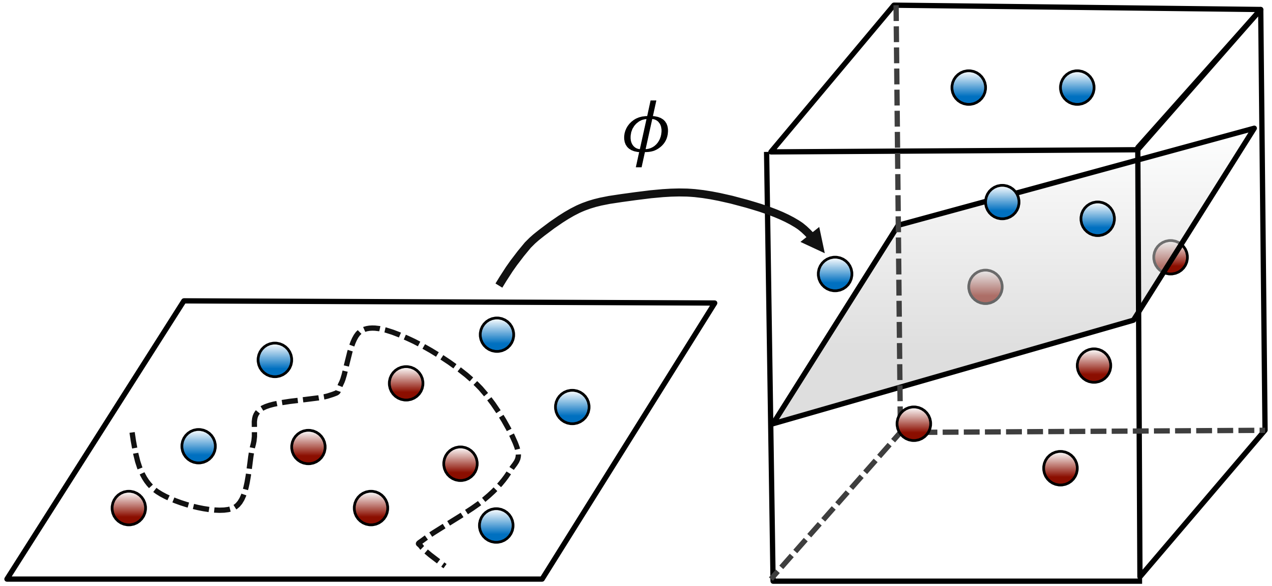
Non-Linear Decision Boundaries with SVM

Non-linear data can be made
linear with higher dimensionality



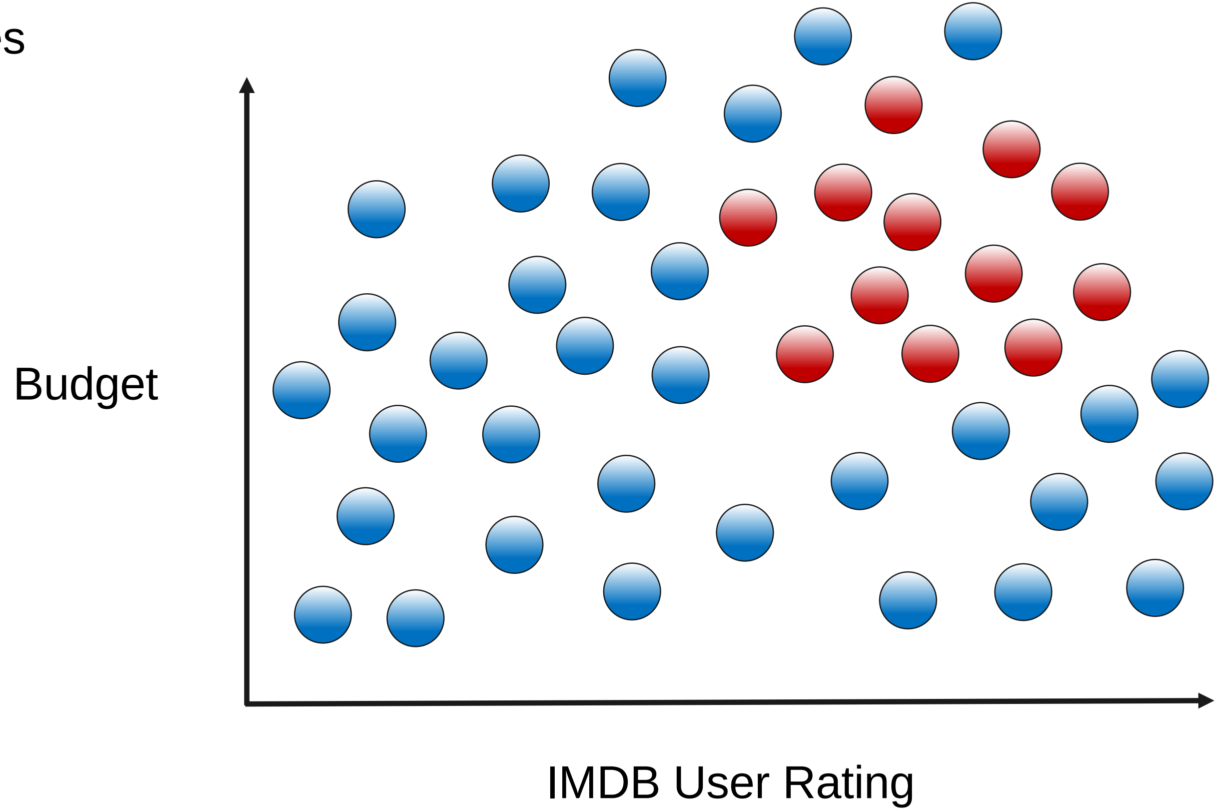
The Kernel Trick

Transform data so it is linearly separable



SVM Gaussian Kernel

Palme d’Or Winners at Cannes



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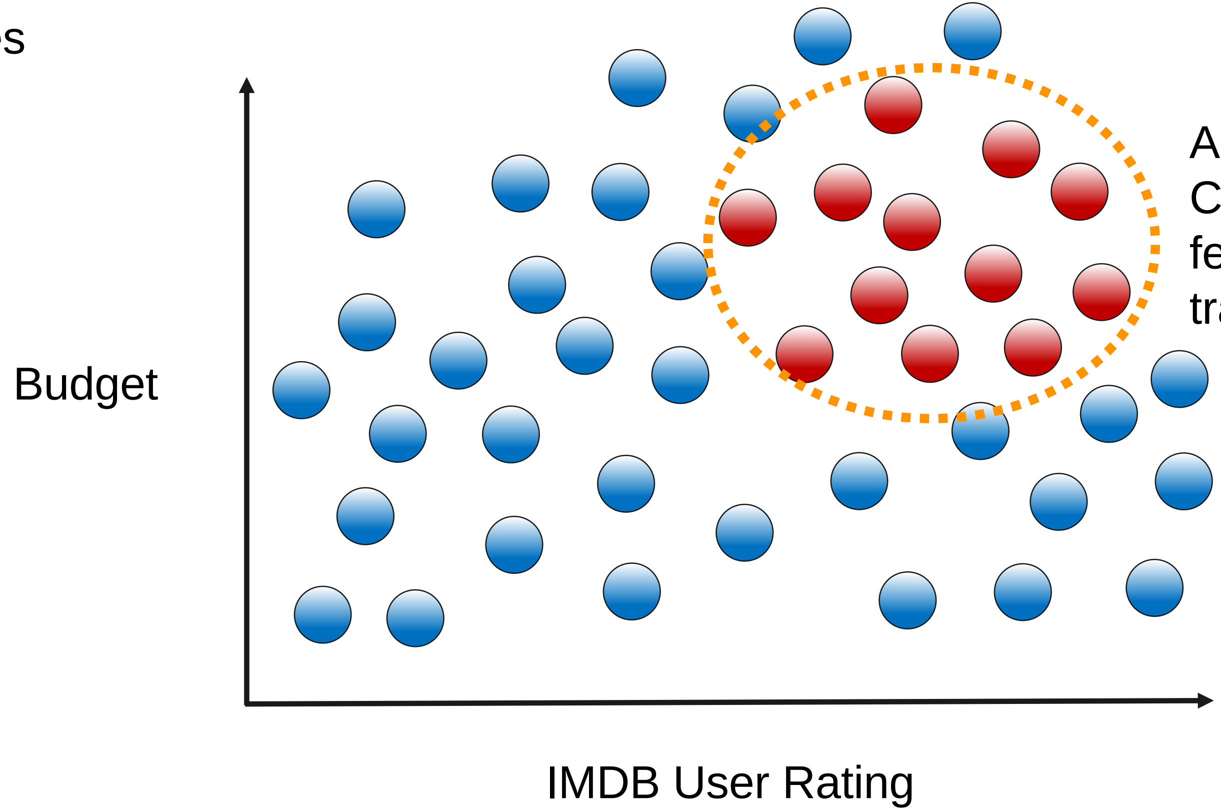


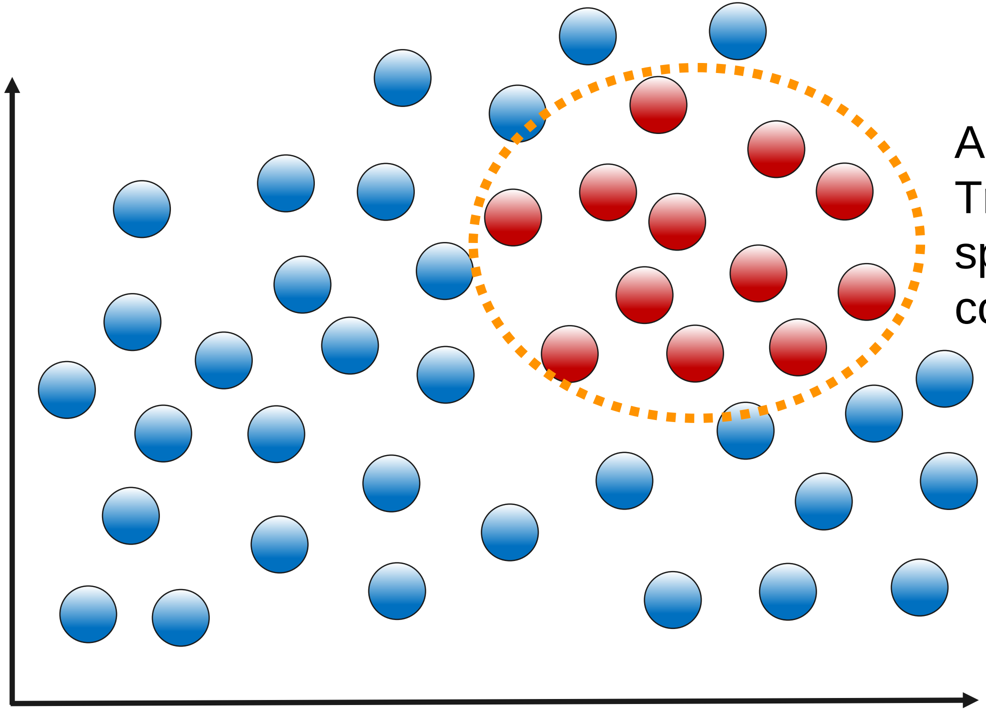
Approach 1:
Create higher order features to transform the data.

$Budget^2$ +
$Rating^2$ +
Budget * Rating +
…

SVM Gaussian Kernel

Palme d’Or Winners at Cannes

Budget

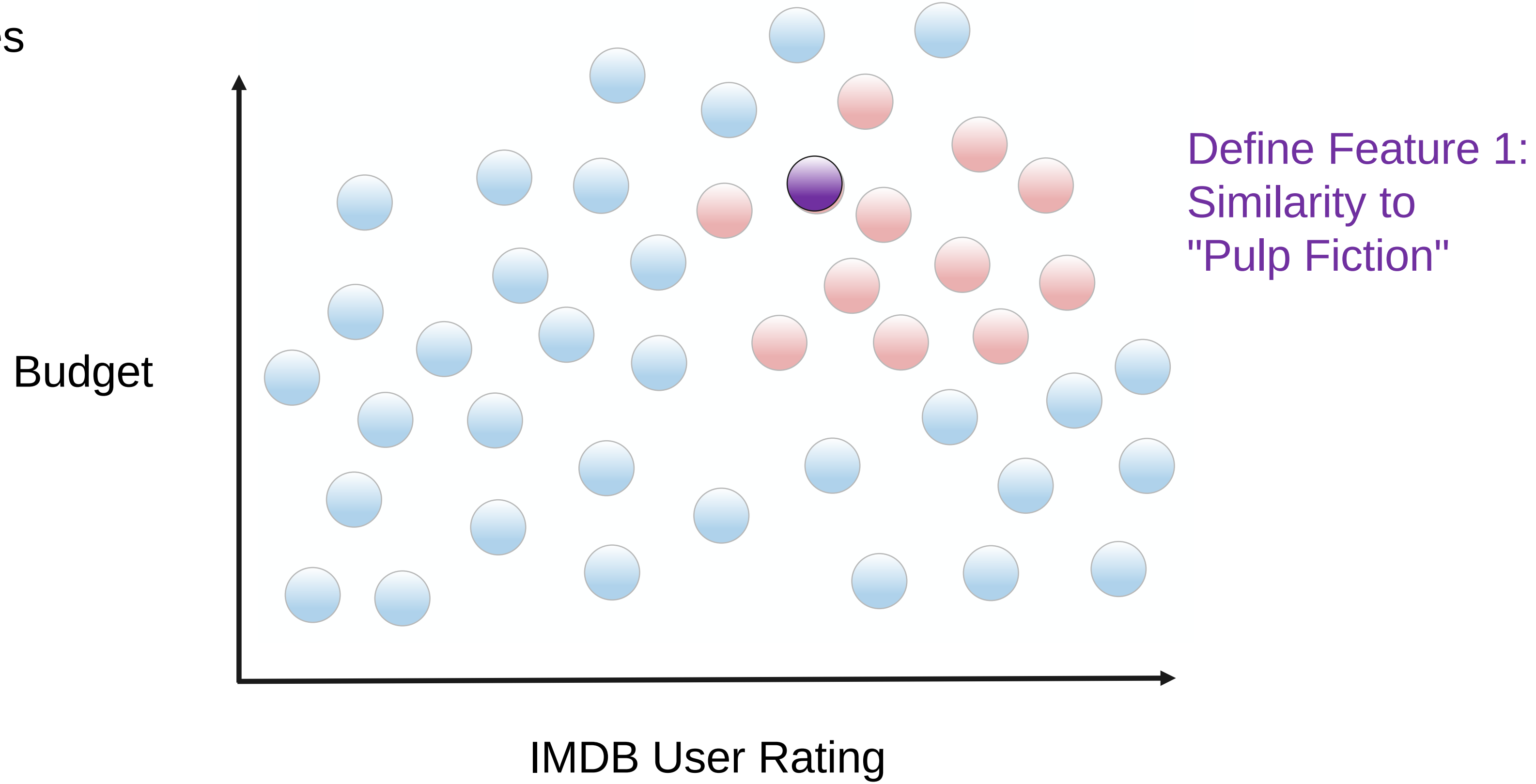


IMDB User Rating

Approach 2: Transform the space to a different coordinate system.

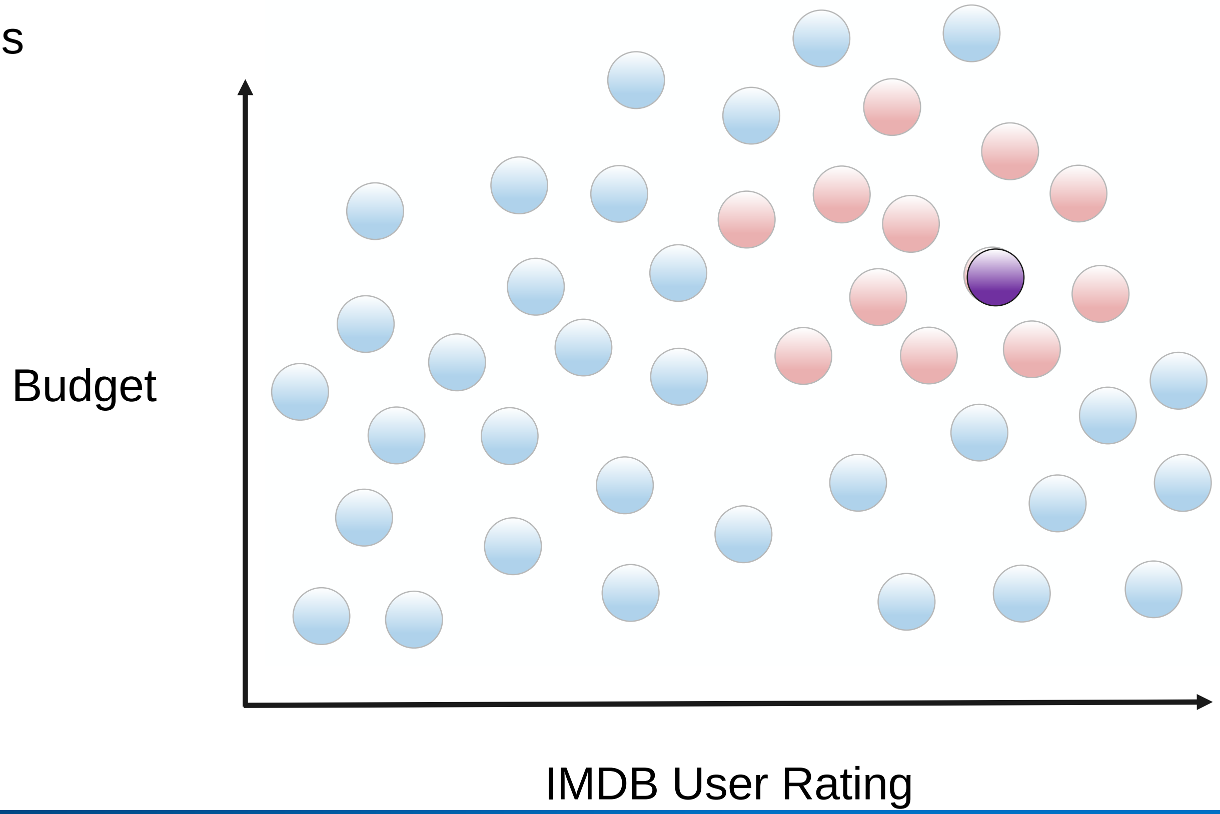
SVM Gaussian Kernel

Palme d'Or Winners at Cannes



SVM Gaussian Kernel

Palme d'Or Winners at Cannes

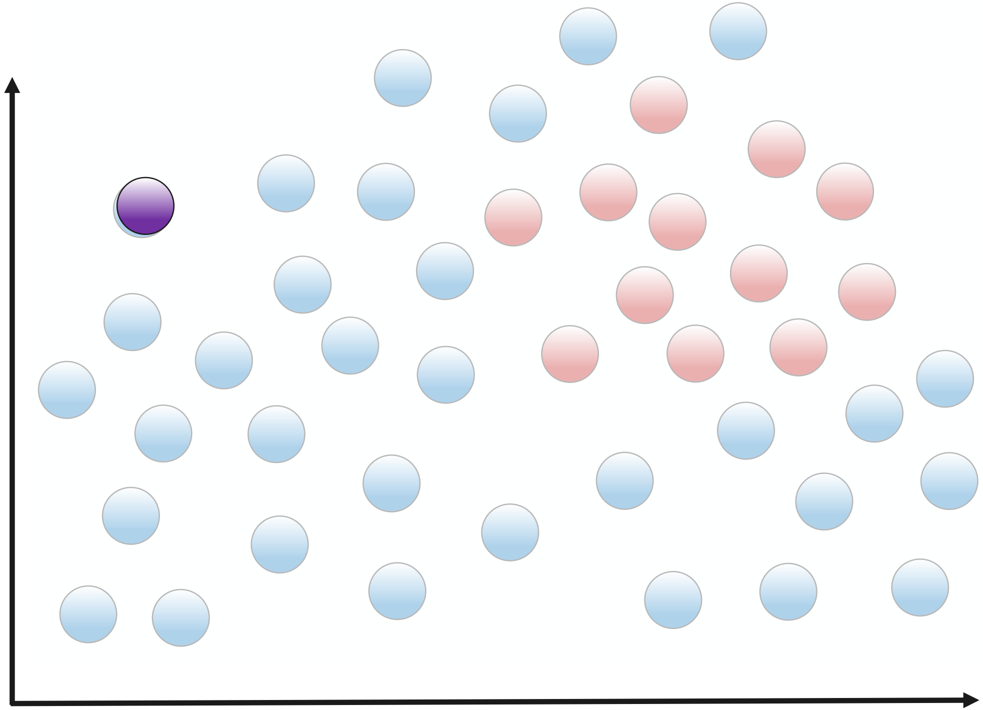


Define Feature 2: Similarity to "Black Swan"

SVM Gaussian Kernel

Palme d’Or Winners at Cannes

Budget



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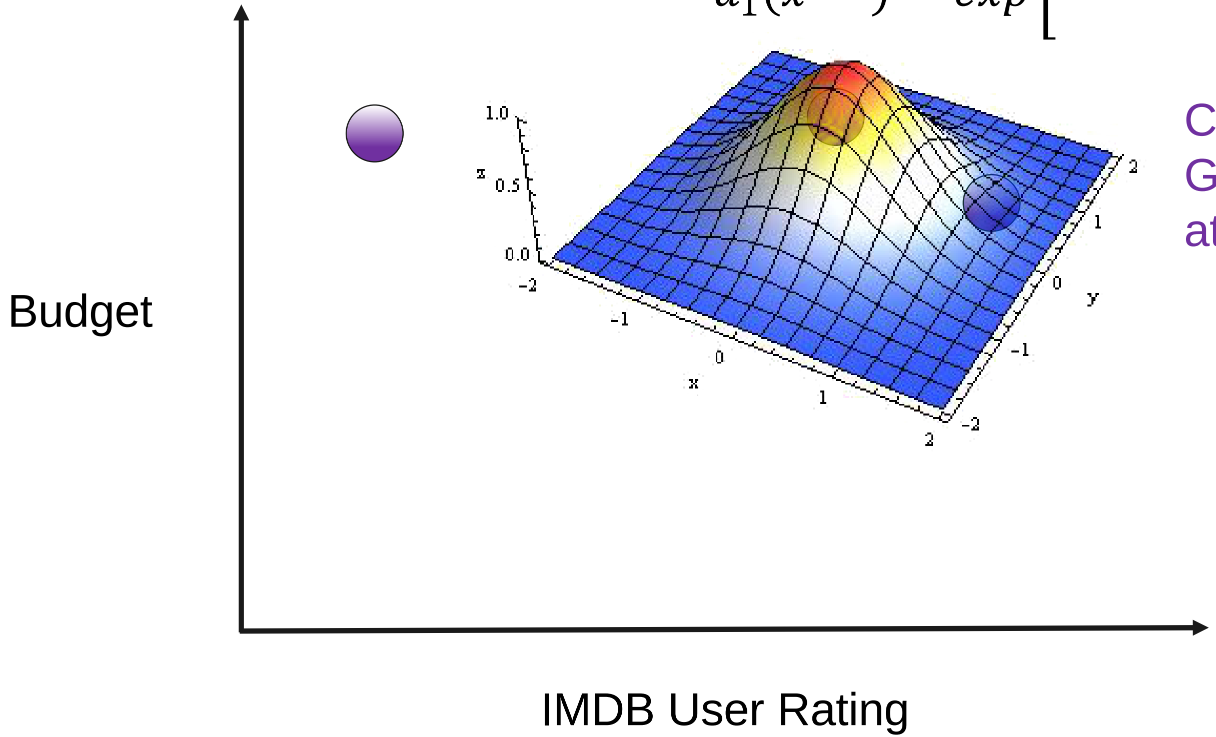
Define Feature 3: Similarity to "Transformers"

SVM Gaussian Kernel

Palme d’Or Winners at Cannes

$$a_1(x^{obs}) = exp\left[\frac{-\sum(x_i^{obs} - x_i^{Pulp\ Fiction})^2}{2\sigma^2}\right]$$



Create a Gaussian function at feature 1

SVM Gaussian Kernel

Palme d'Or Winners at Cannes

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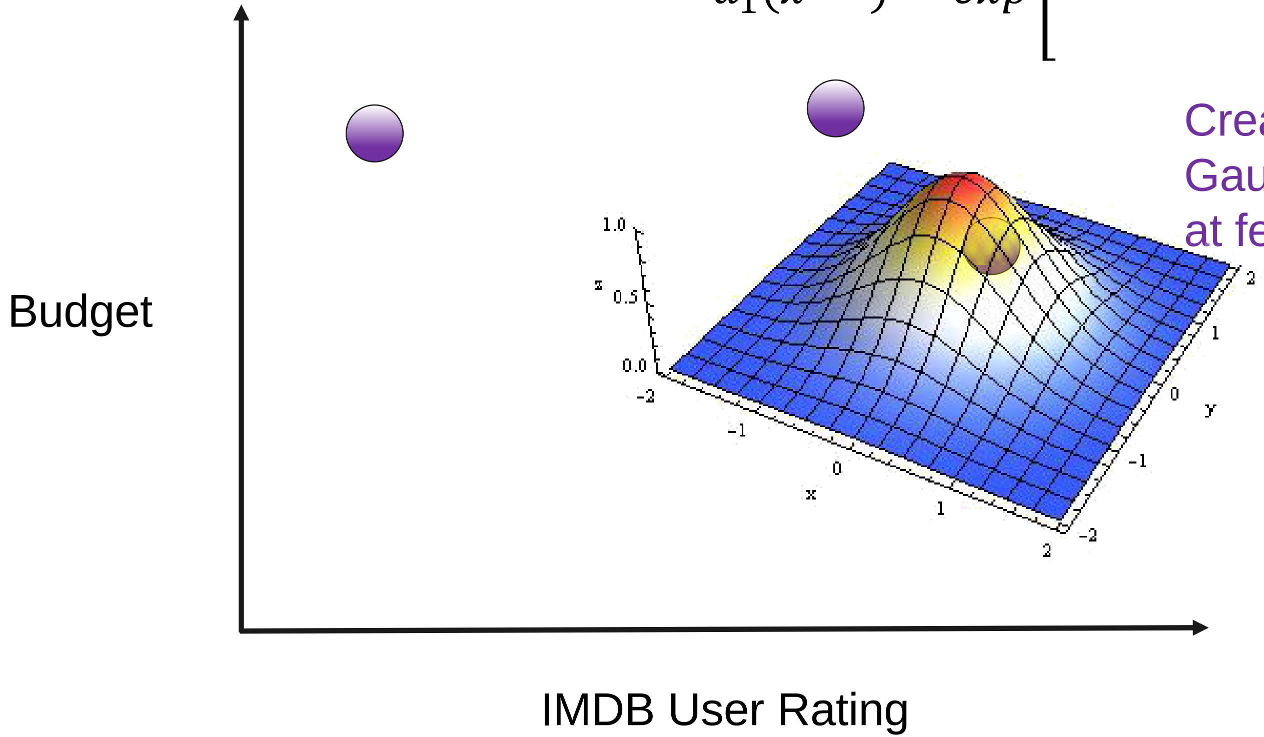
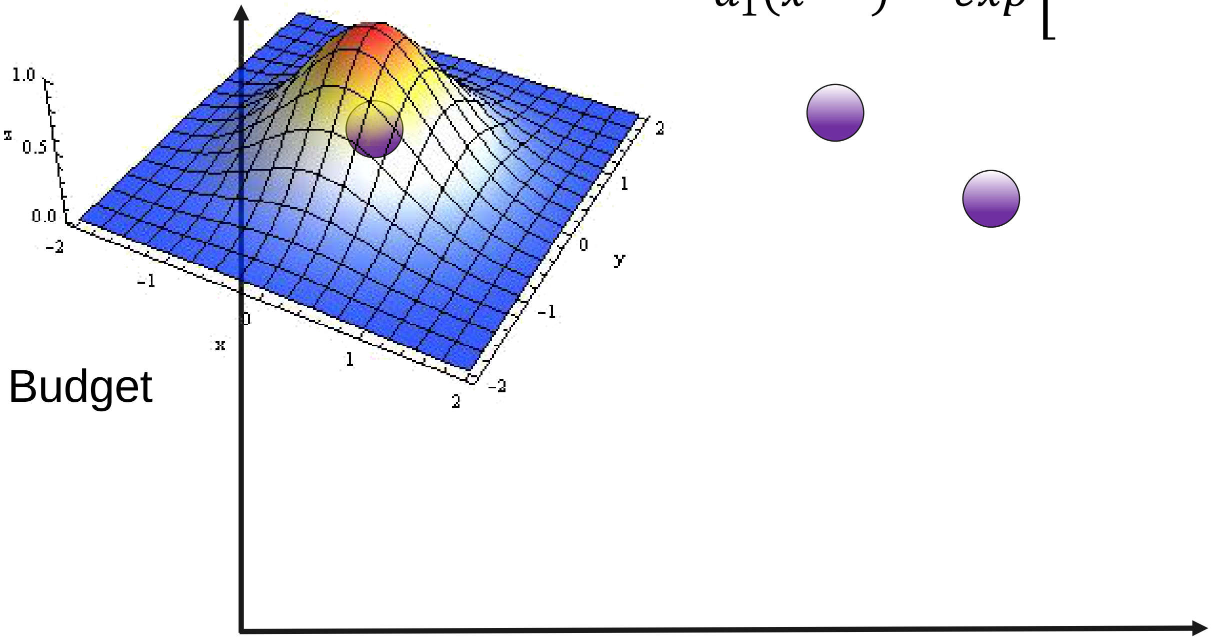


Create a Gaussian function at feature 2

SVM Gaussian Kernel

Palme d'Or Winners at Cannes

$$a_1(x^{obs}) = exp\left[\frac{-\sum(x_i^{obs} - x_i^{Transformers})^2}{2\sigma^2}\right]$$

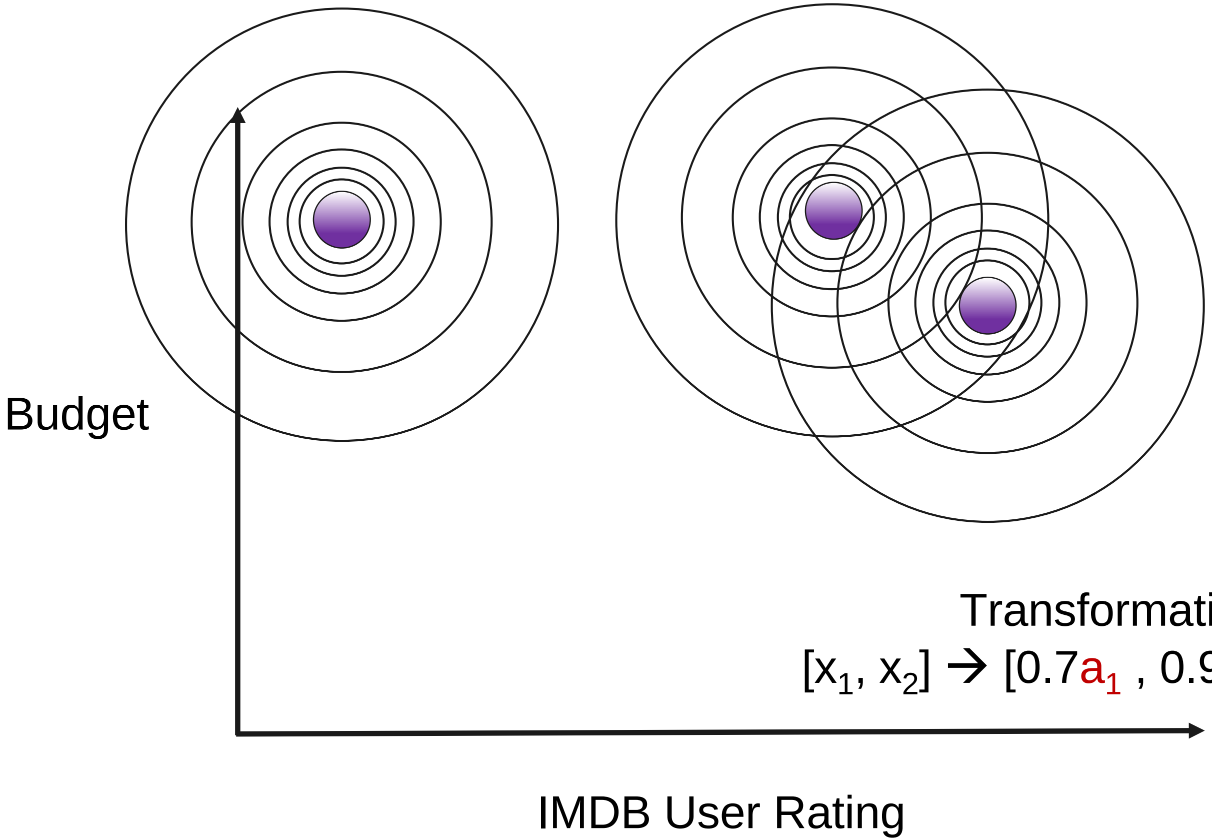


Budget

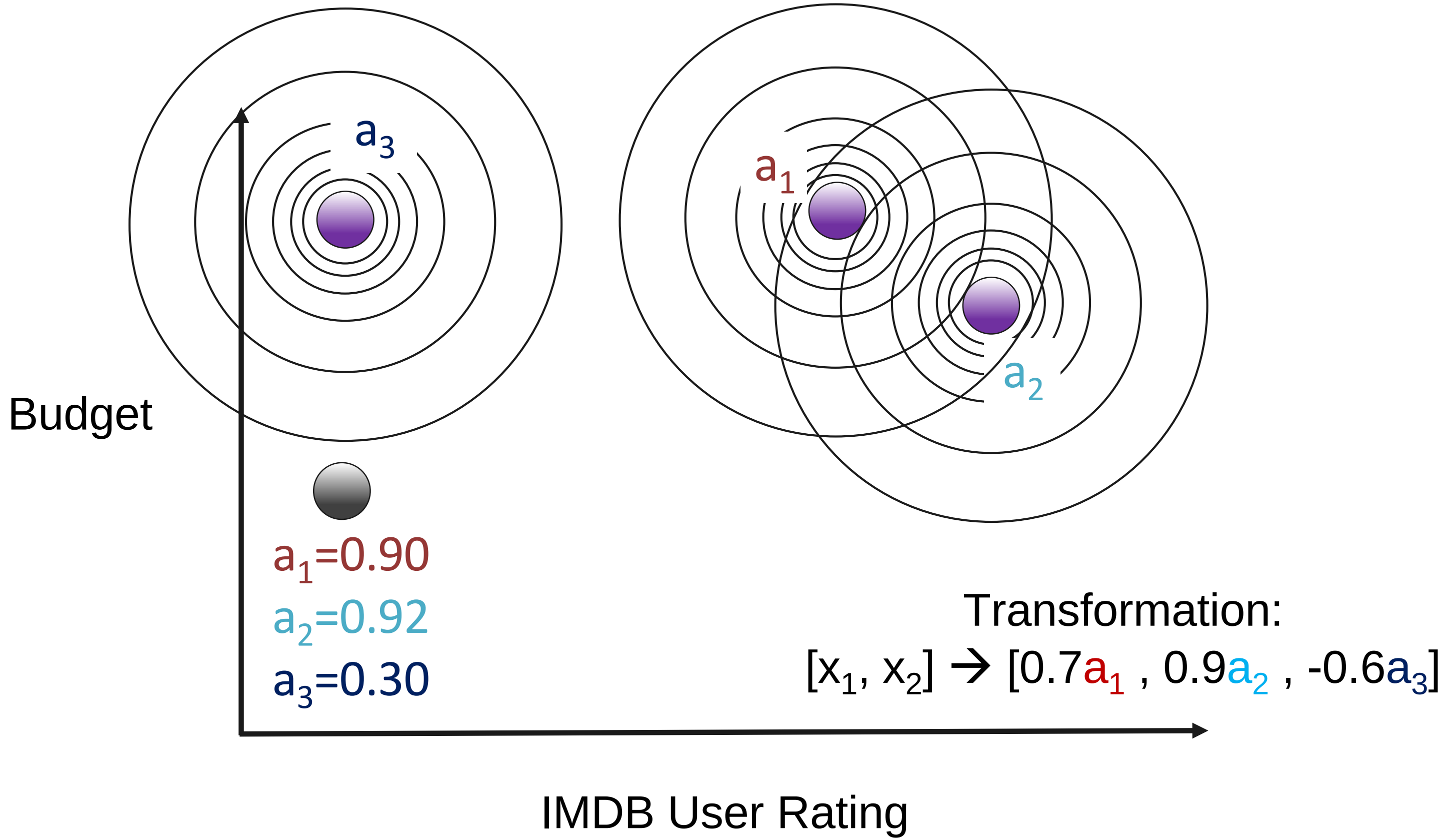
IMDB User Rating

Create a Gaussian function at feature 3

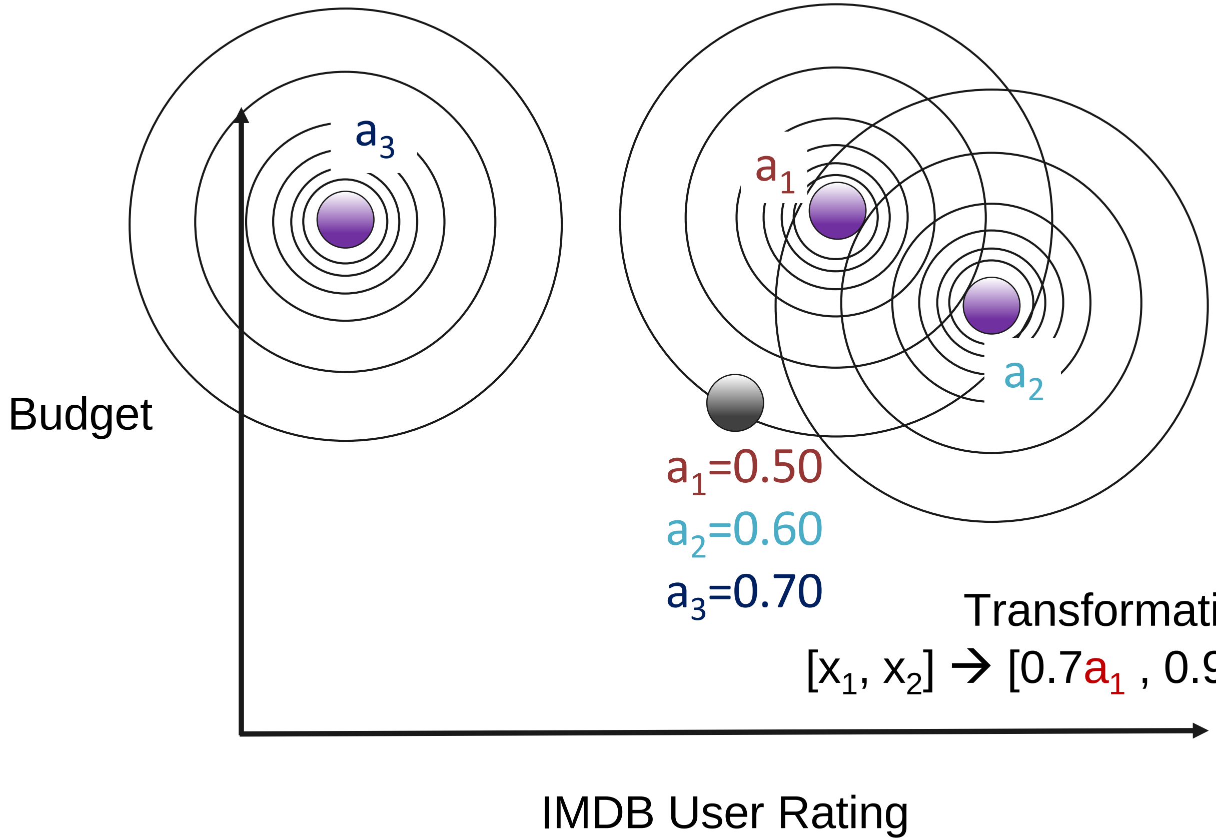
SVM Gaussian Kernel



SVM Gaussian Kernel



SVM Gaussian Kernel



Transformation:

$[x_1, x_2] \rightarrow [0.7a_1 , 0.9a_2 , -0.6a_3]$

SVM Gaussian Kernel

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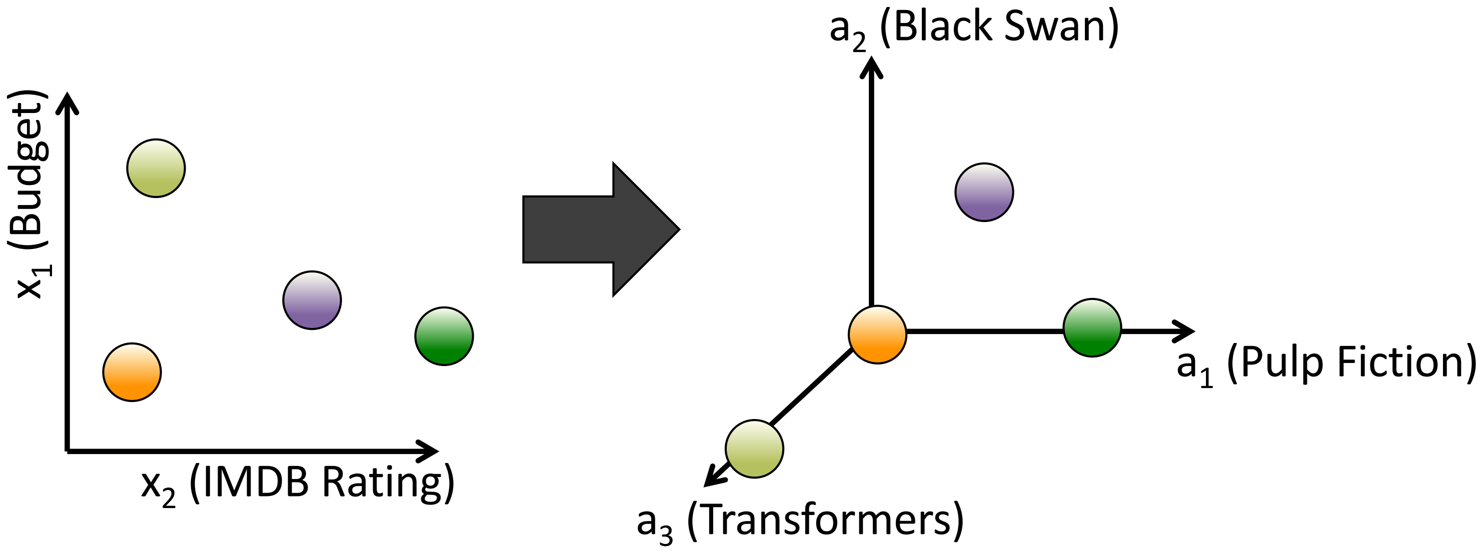
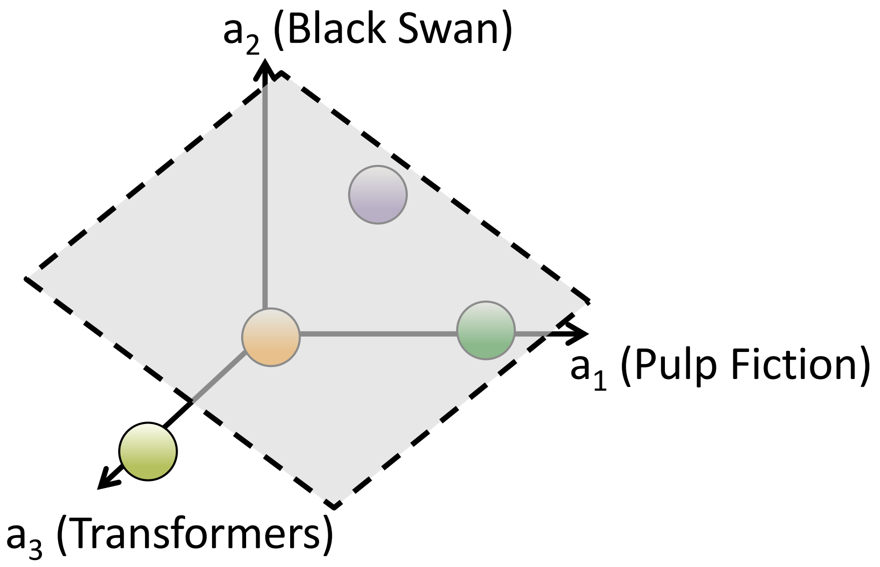


Classification in the New Space

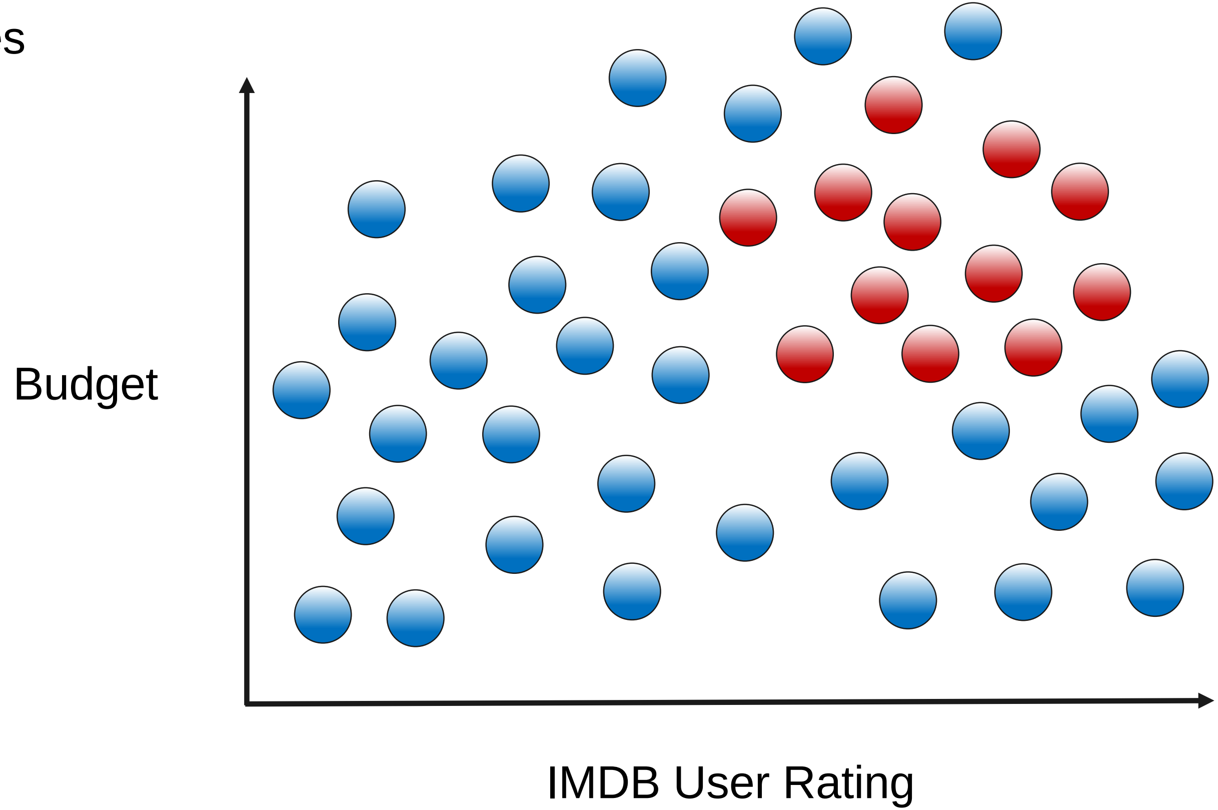
Transformation:

$[x_1, x_2] \rightarrow [0.7a_1\ ,\ 0.9a_2\ ,\ -0.6a_3]$



SVM Gaussian Kernel

Palme d'Or Winners at Cannes



SVM Gaussian Kernel

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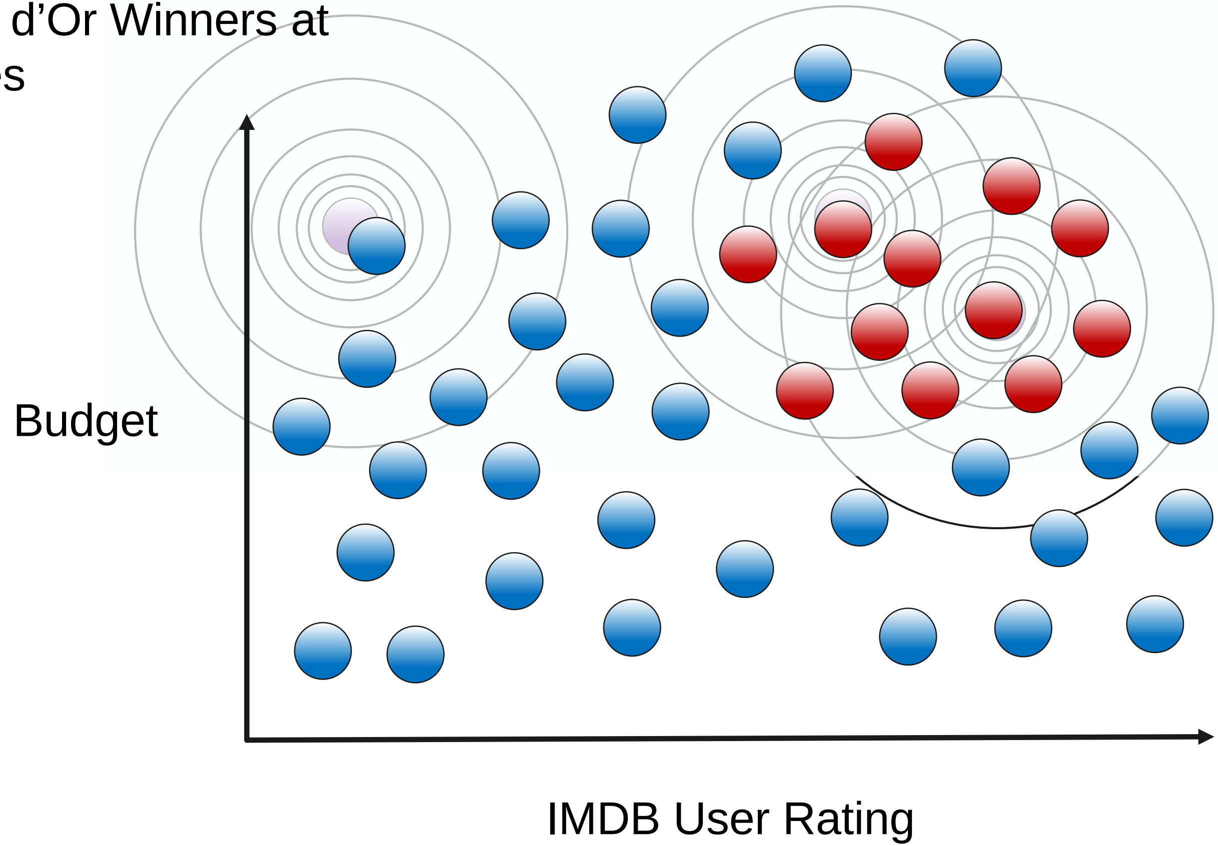
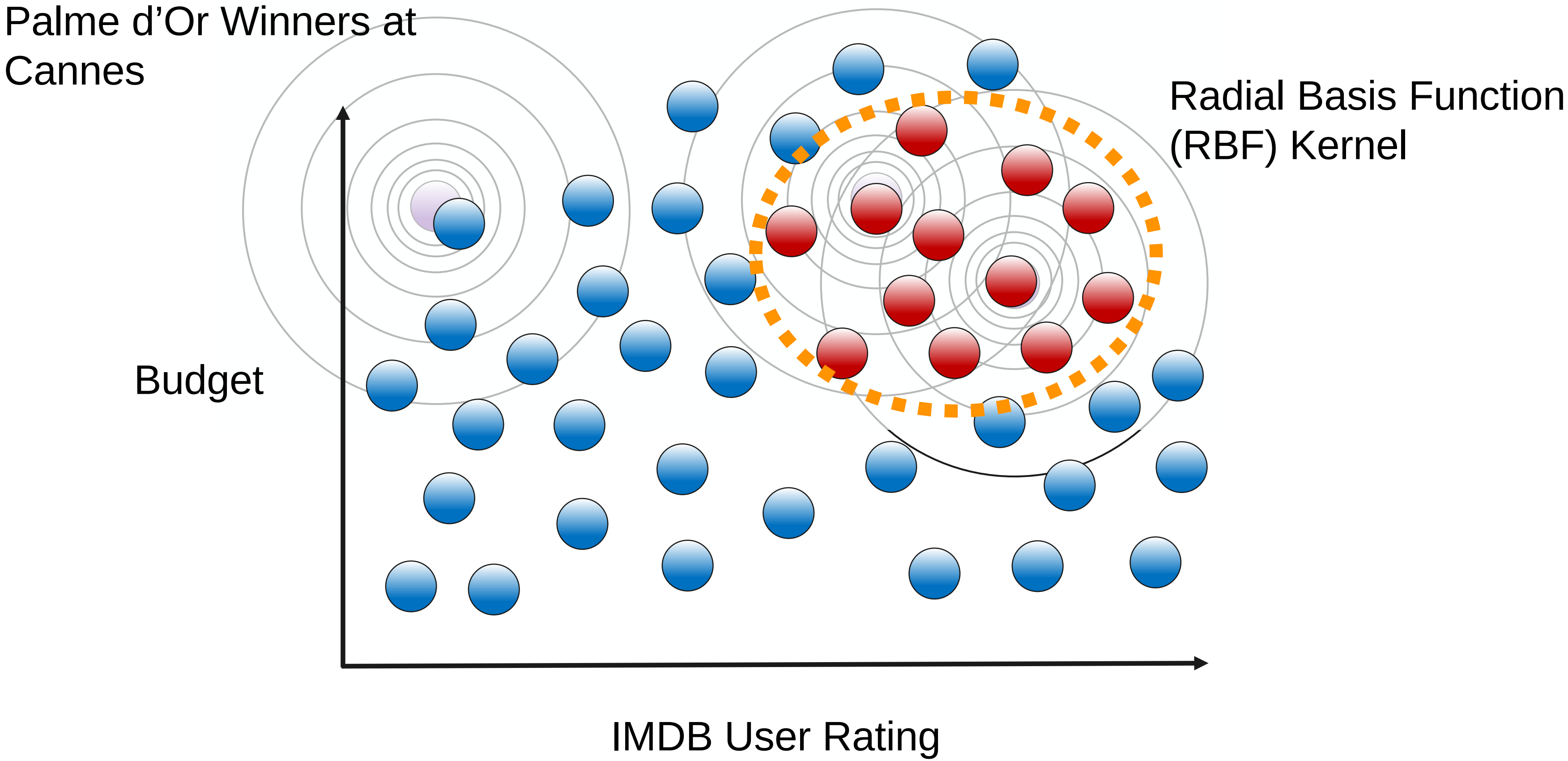


SVM Gaussian Kernel



SVMs with Kernels: The Syntax

Import the class containing the classification method

```
from sklearn.svm import SVC
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SVMs with Kernels: The Syntax

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Create an instance of the class

```
rbfSVC = SVC(kernel='rbf', gamma=1.0, C=10.0)
```

SVMs with Kernels: The Syntax

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from sklearn.svm import SVC
```

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```
rbfSVC = SVC(kernel='rbf', gamma=1.0, C=10.0)
```

set kernel and associated coefficient (gamma)

e

SVMs with Kernels: The Syntax

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```

"C" is penalty associated with the error term

e

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```

Fit the instance on the data and then predict the expected value

```
rbfSVC = rbfSVC.fit(X_train, y_train)
y_predict = rbfSVC.predict(X_test)
```

SVMs with Kernels: The Syntax

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Tune kernel and associated parameters with cross-validation.

Feature Overload

Problem

SVMs with RBF Kernels are very slow to train with lots of features or data

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Solution

Construct approximate kernel map with SGD using Nystroem or RBF sampler

Feature Overload

Problem

SVMs with RBF Kernels are very slow to train with lots of features or data

Solution

Construct approximate kernel map with SGD using Nystroem or RBF sampler. Fit a linear classifier.

Faster Kernel Transformations: The Syntax

Import the class containing the classification method

```
from sklearn.kernel_approximation import Nystroem
```

Create an instance of the class

```
nystroemSVC = Nystroem(kernel='rbf', gamma=1.0,
                       n_components=100)
```

Fit the instance on the data and transform

```
X_train = nystroemSVC.fit_transform(X_train)
X_test = nystroemSVC.transform(X_test)
```

Tune kernel parameters and components with cross-validation.

Faster Kernel Transformations: The Syntax

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```

Create an instance of the class

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```

multiple non-linear kernels can be used

Fit the instance on the data and transform

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kernel and gamma are identical to SVC

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```

n_components is number of samples

Fit the instance on the data and transform

```
X_train = nystroemSVC.fit_transform(X_train)
X_test = nystroemSVC.transform(X_test)
```

Tune kernel parameters and components with cross-validation.

Faster Kernel Transformations: The Syntax

Import the class containing the classification method

```
from sklearn.kernel_approximation import RBFsampler
```

Create an instance of the class

```
rbfSample = RBFsampler(gamma=1.0,
                       n_components=100)
```

Fit the instance on the data and transform

```
X_train = rbfSample.fit_transform(X_train)
X_test = rbfSample.transform(X_test)
```

Tune kernel parameters and components with cross-validation.

Faster Kernel Transformations: The Syntax

Import the class containing the classification method

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```

Create an instance of the class

```
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                       n_components=100)
```

RBF is only kernel that can be used

Fit the instance on the data and transform

```
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Tune kernel parameters and components with cross-validation.

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```

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```
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```

parameter names are identical to previous

Fit the instance on the data and transform

```
X_train = rbfSample.fit_transform(X_train)
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```

Tune kernel parameters and components with cross-validation.

When to Use Logistic Regression vs SVC

Features	Data	Model Choice
Many (~10K	Small (1K rows)	Simple, Logistic or LinearSVC
Features)	Medium (~10k rows)	SVC with RBF
Few (<100 Features)	Many (>100K Points)	Add features, Logistic, LinearSVC
Few (<100 Features)		or Kernel Approx.

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