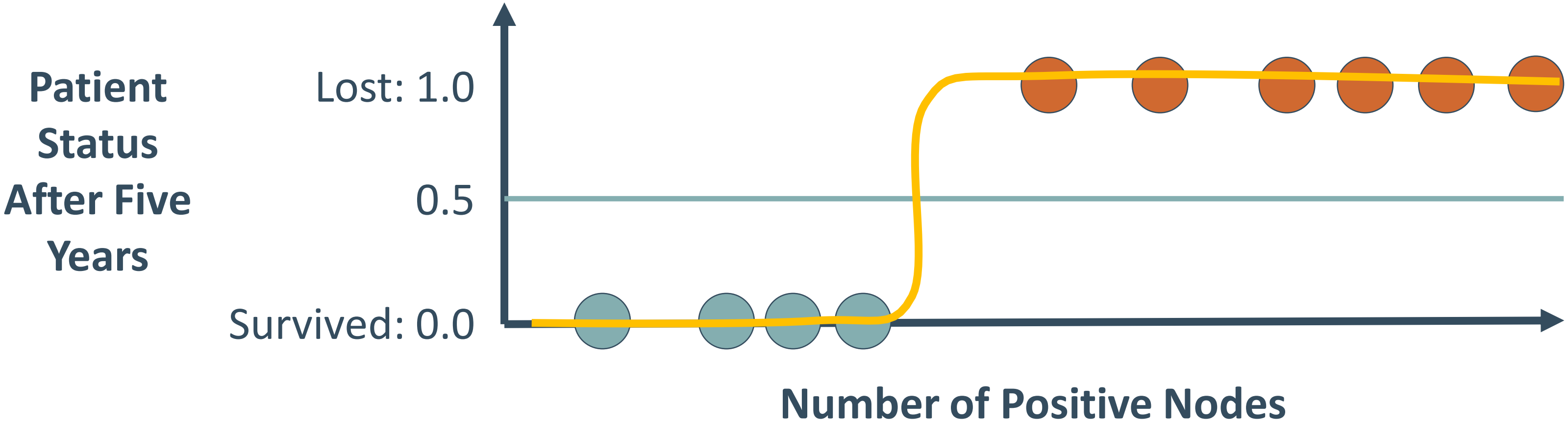
Intel Nervana™ AI Academy

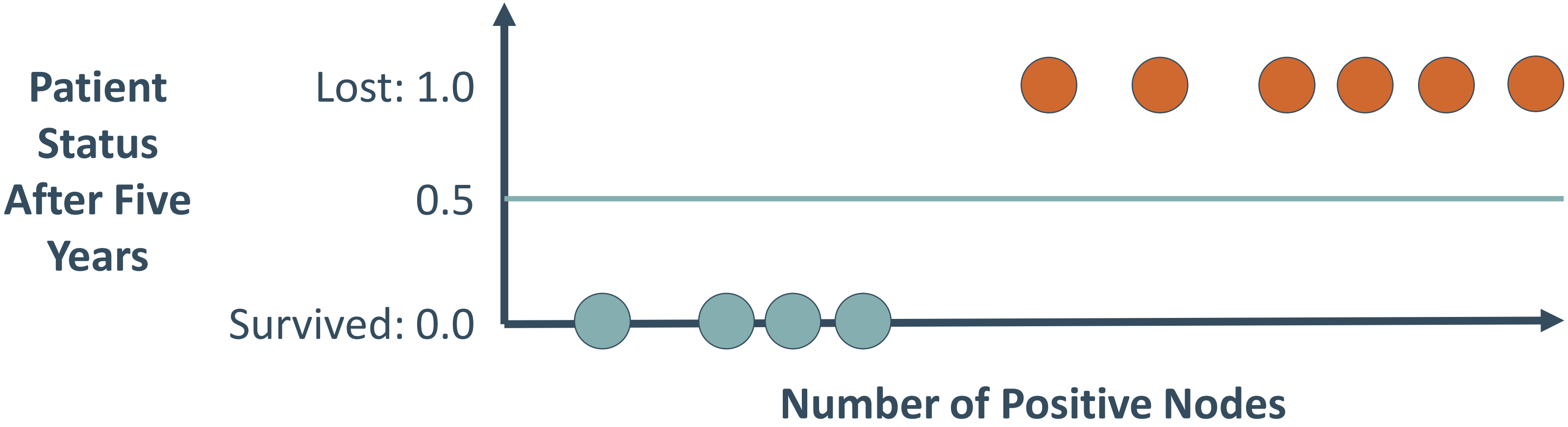
Support Vector Machines

Relationship to Logistic Regression



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

Support Vector Machines (SVM)



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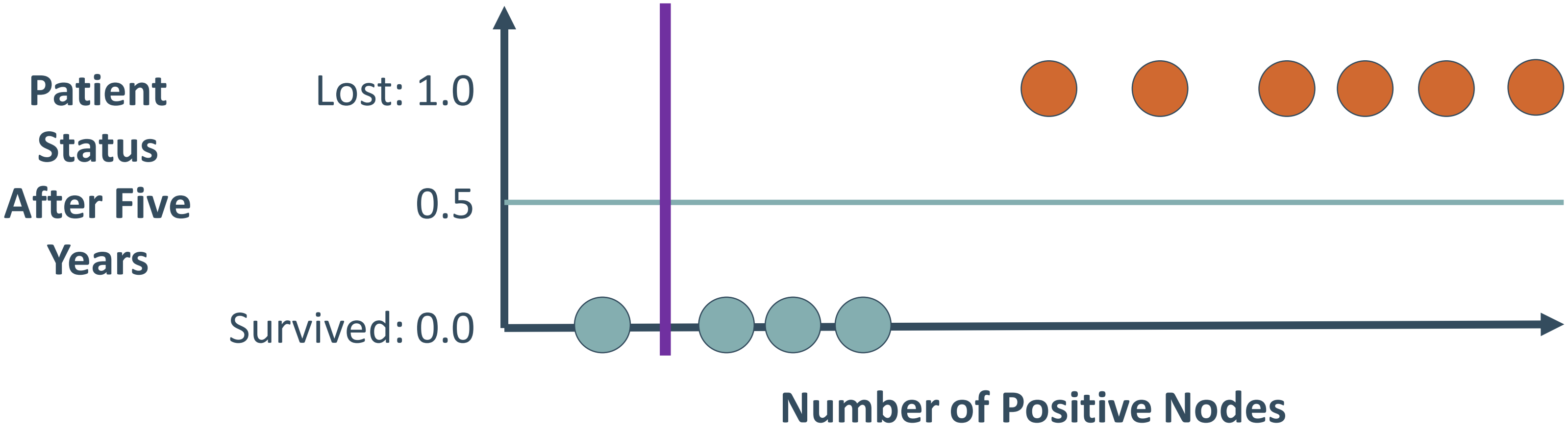
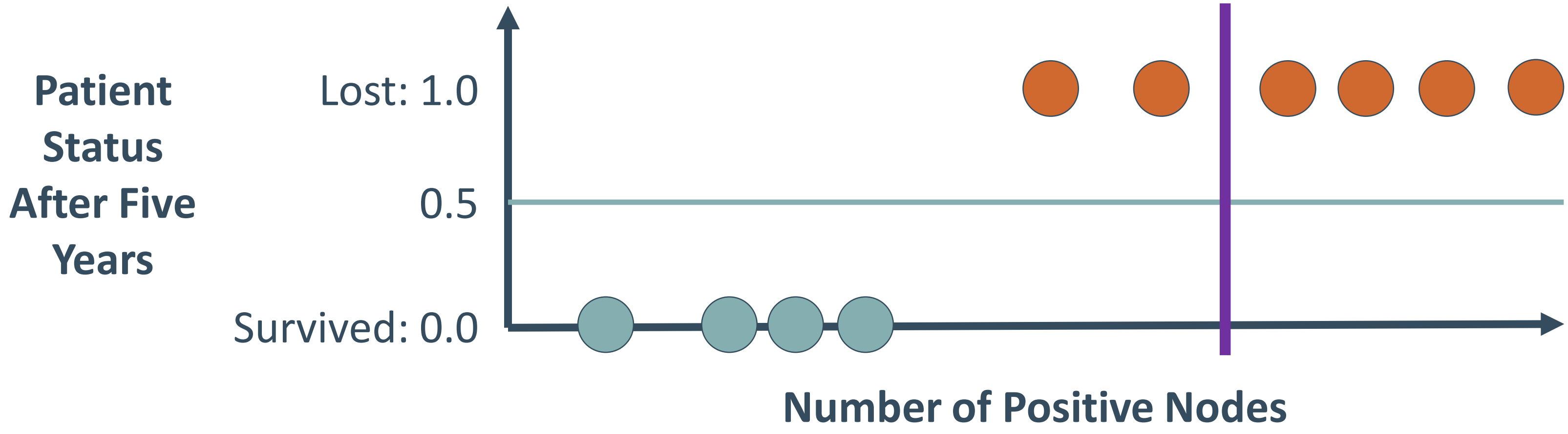


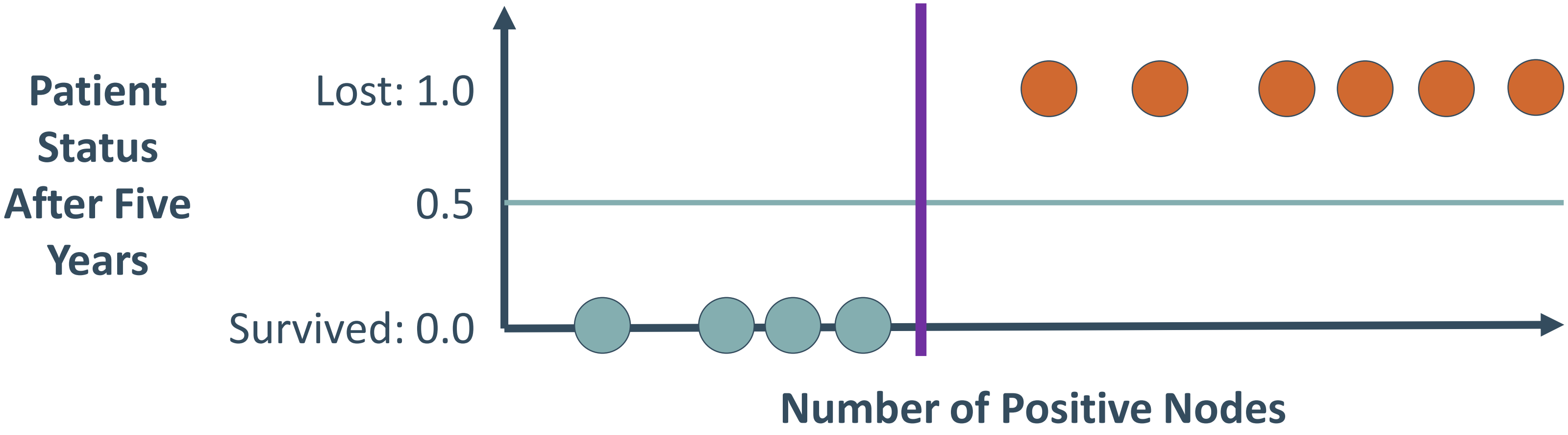
Three misclassifications

Support Vector Machines (SVM)



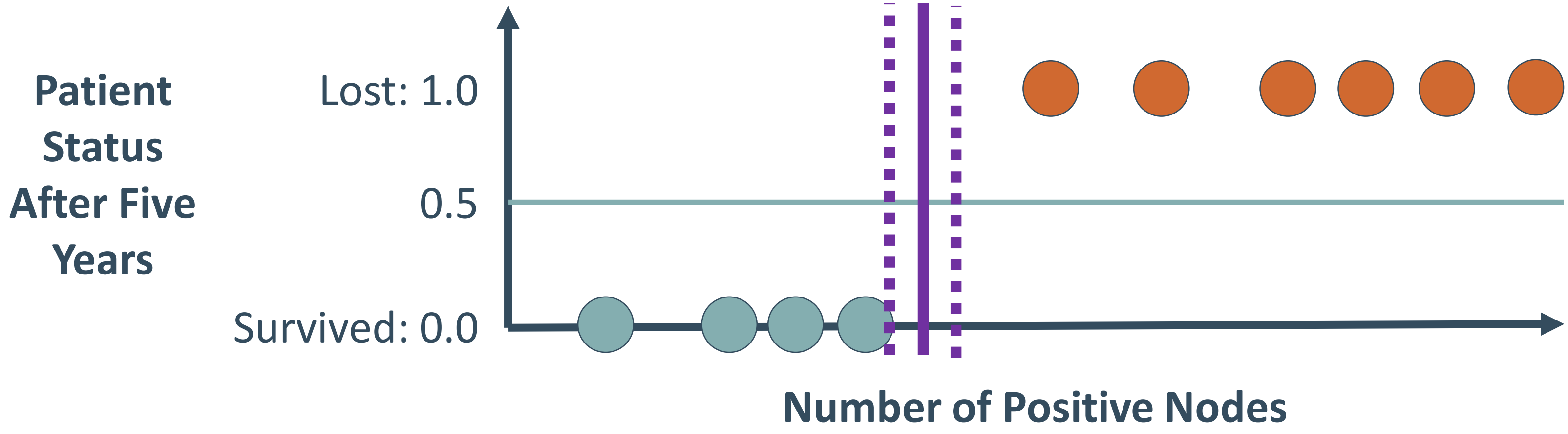
Two misclassifications

Support Vector Machines (SVM)



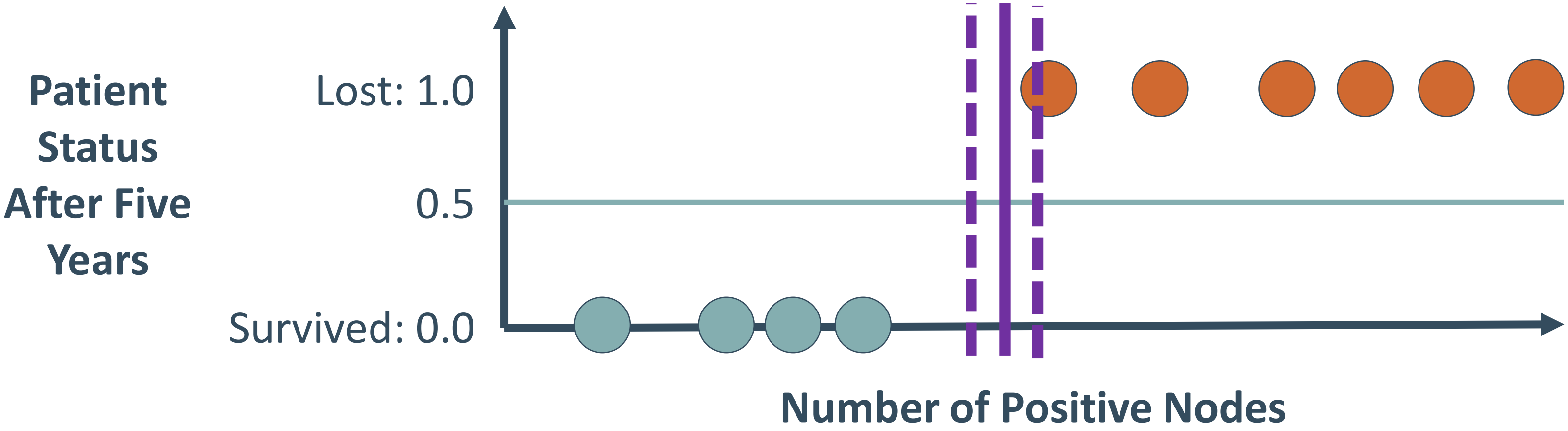
No misclassifications

Support Vector Machines (SVM)



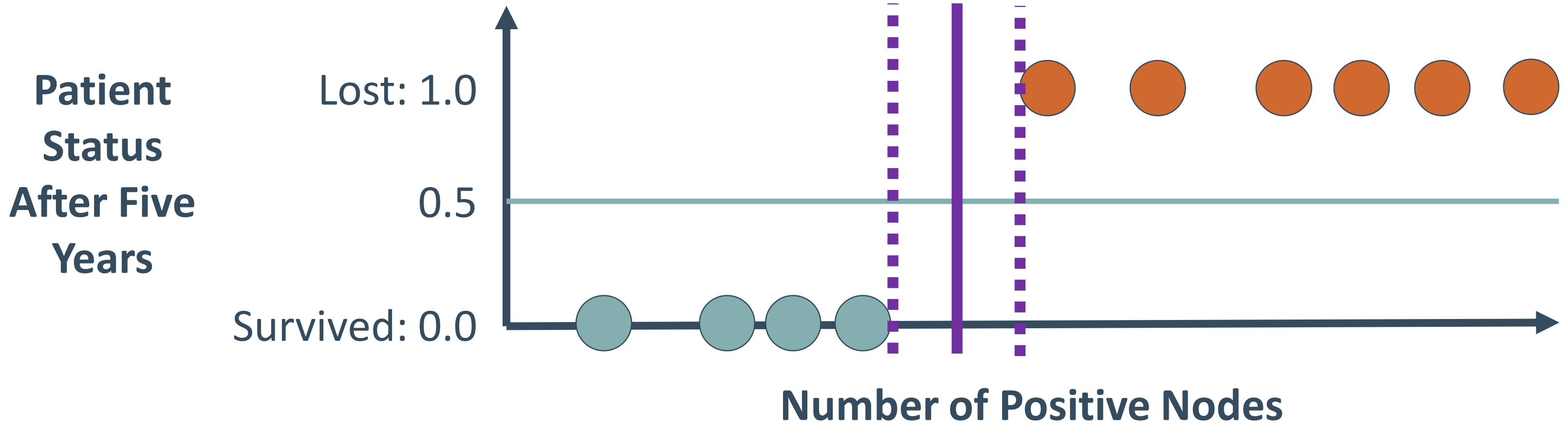
No misclassifications—but is this the best position?

Support Vector Machines (SVM)



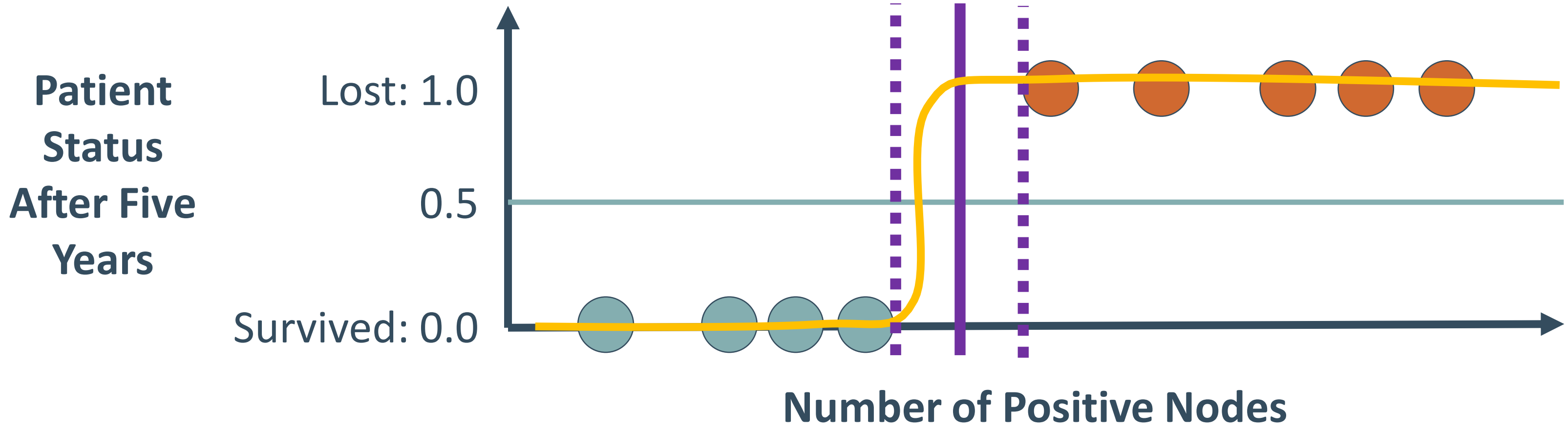
No misclassifications—but is this the best position?

Support Vector Machines (SVM)



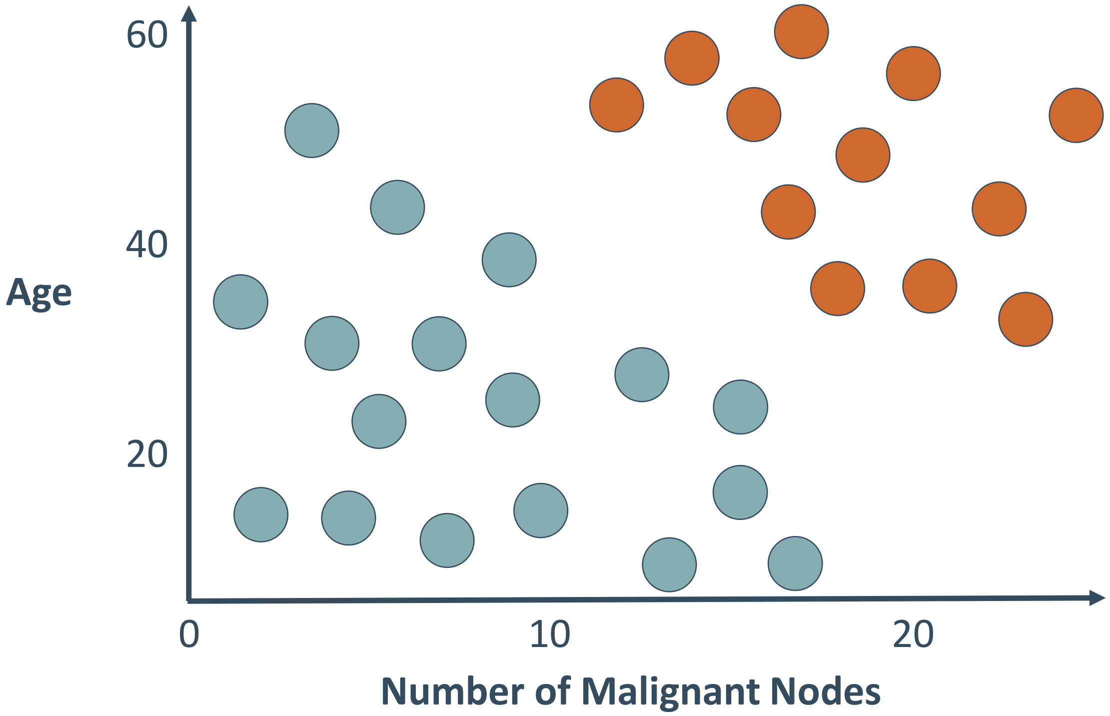
Maximize the region between classes.

Similarity Between Logistic Regression and SVM



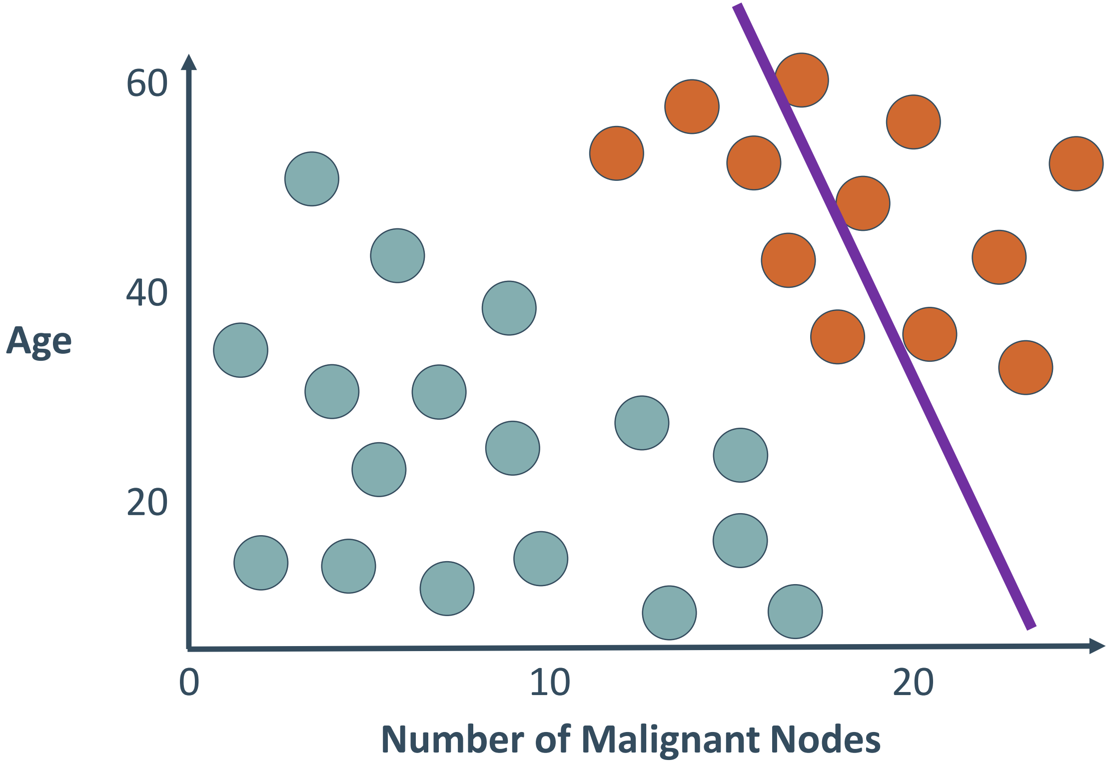
Classification with SVMs

Two features (nodes, age)
Two labels (survived, lost)



Classification with SVMs

Find the line that best separates classes.



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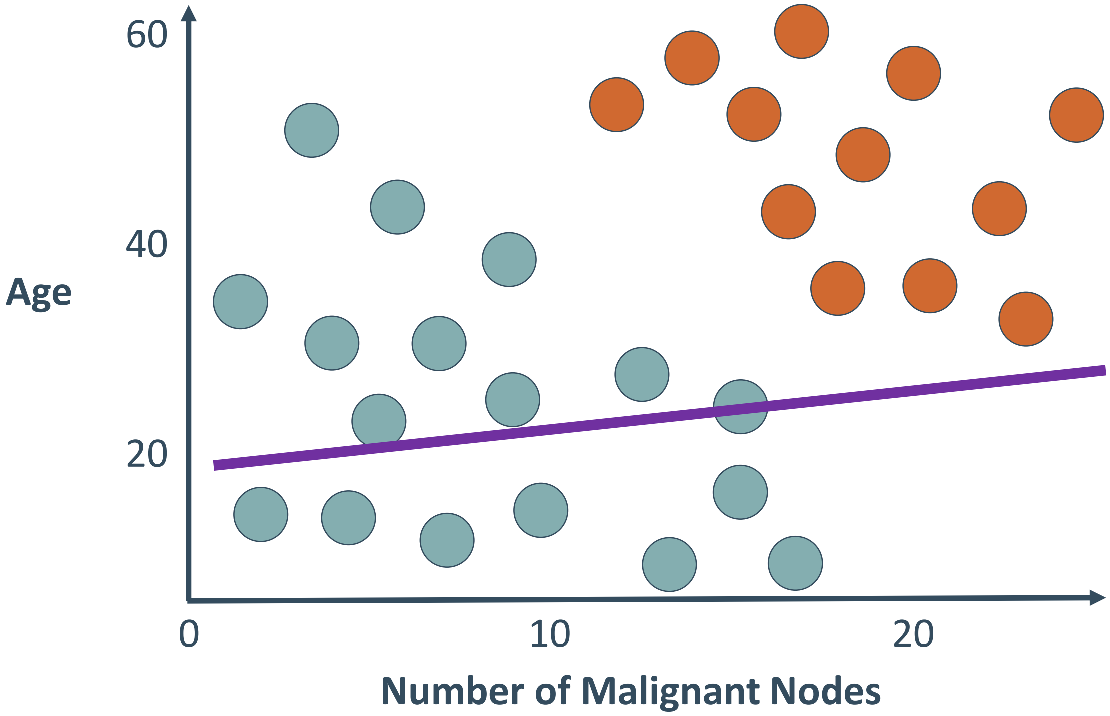

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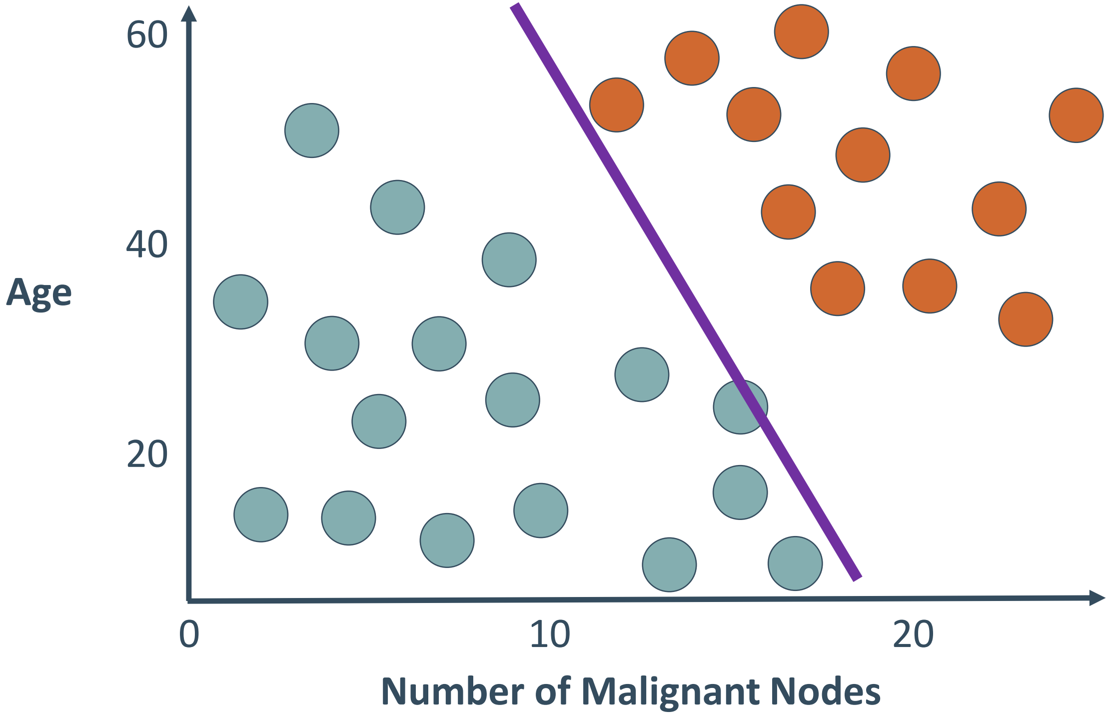

Classification with SVMs

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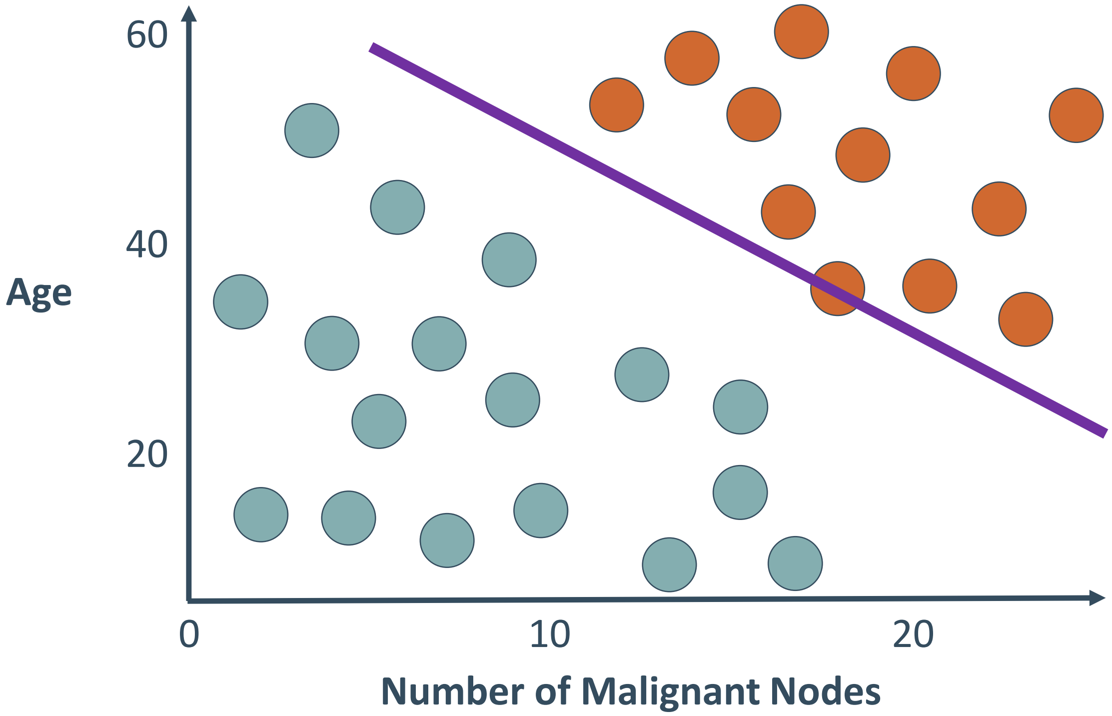
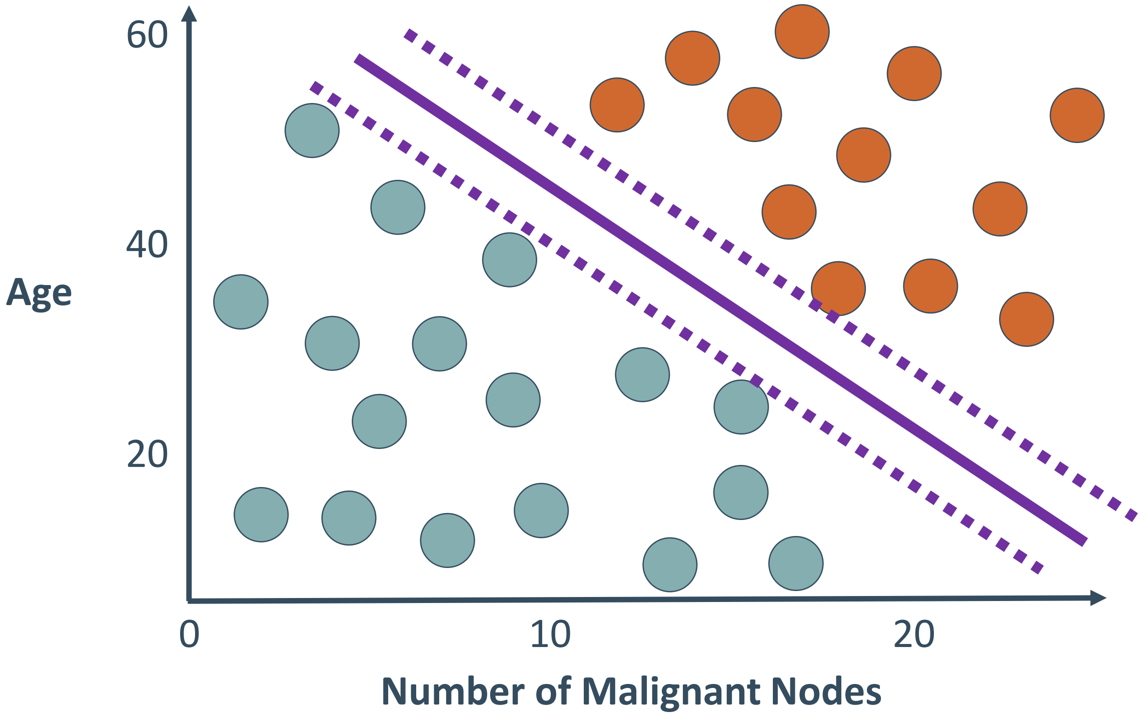
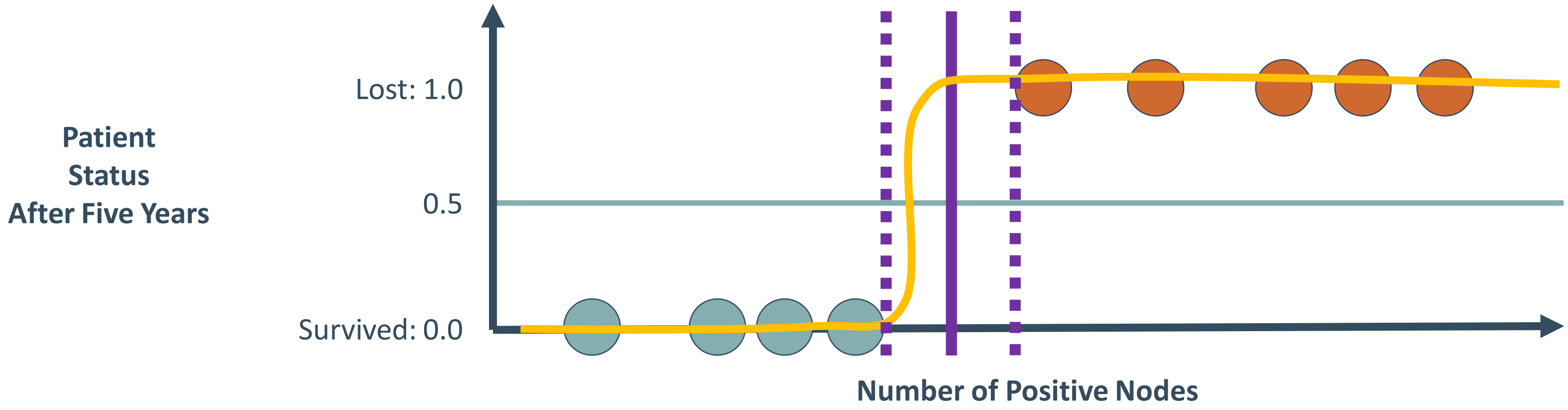


Classification with SVMs

Also, include the largest boundary possible.



Logistic Regression vs SVM Cost Functions



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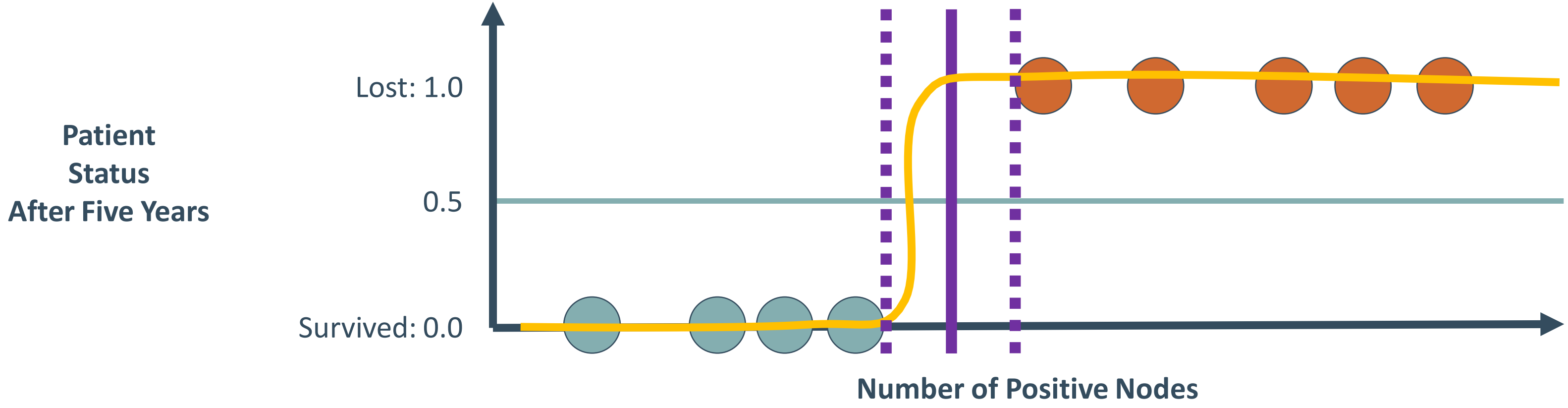

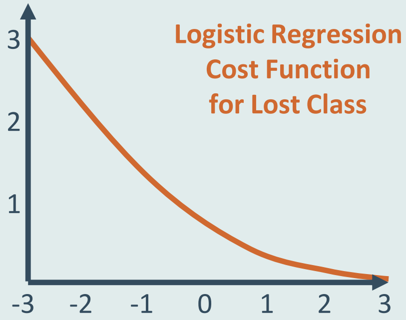

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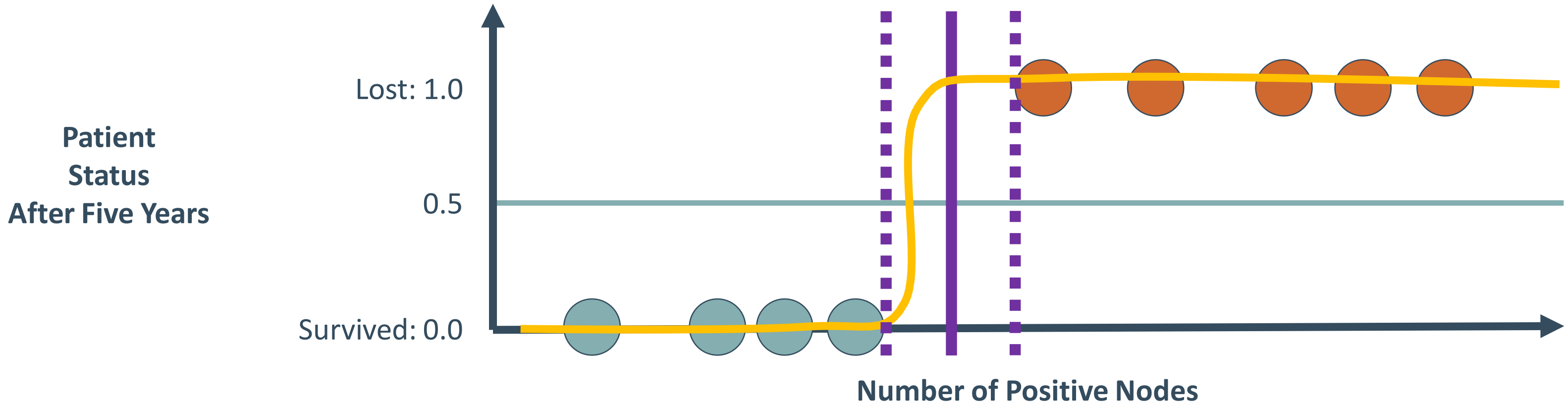
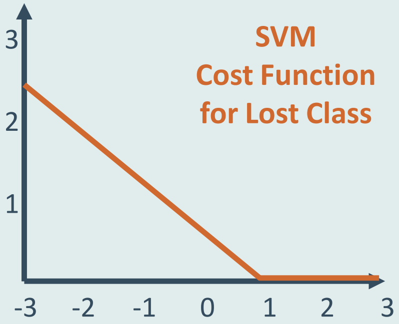
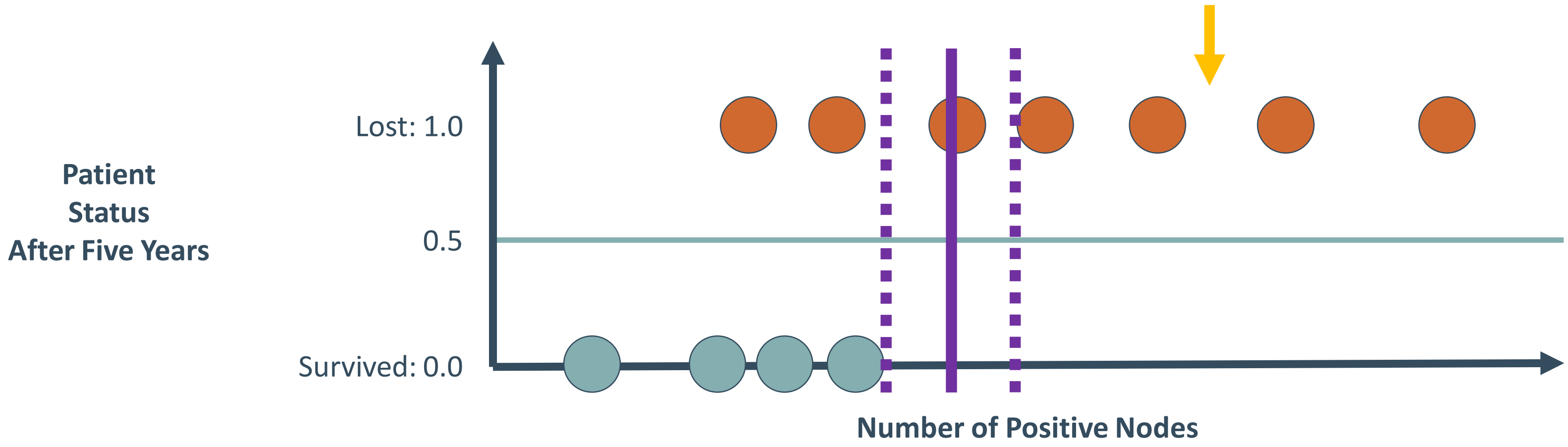
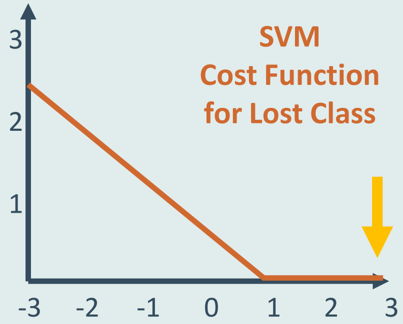




The SVM Cost Function





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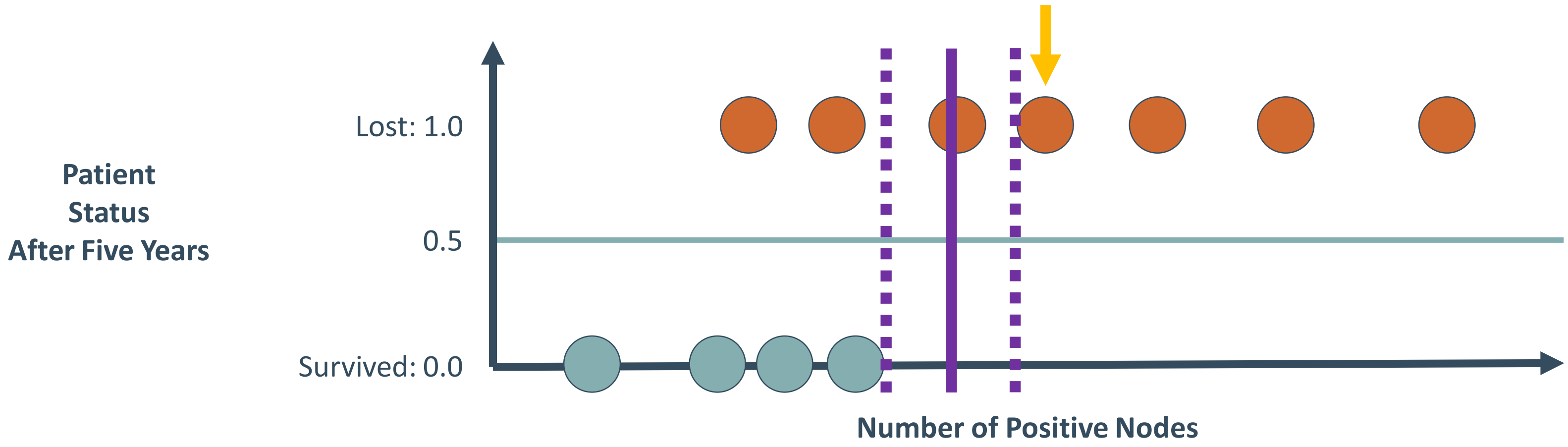

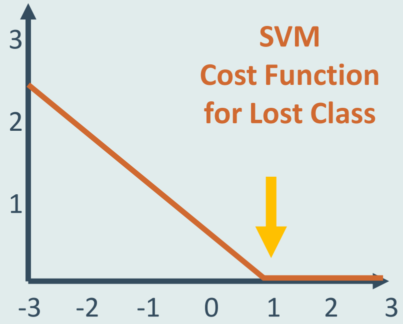

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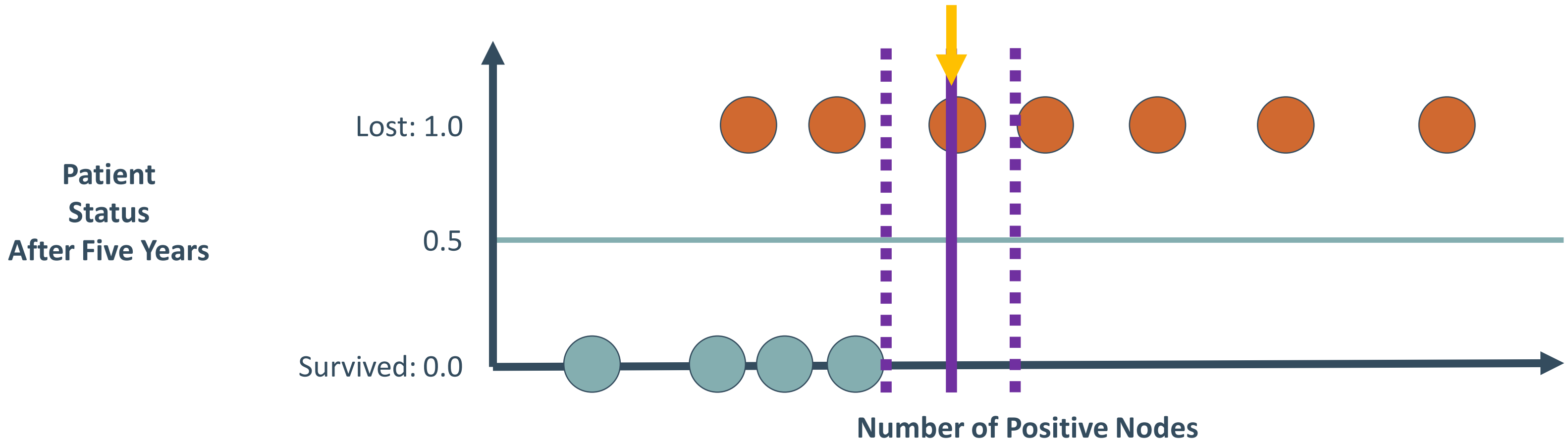

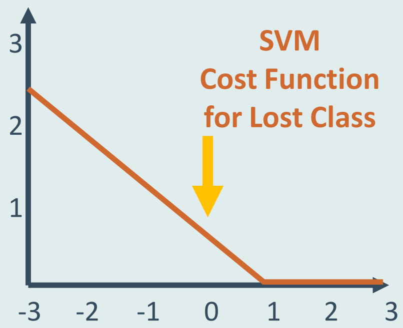

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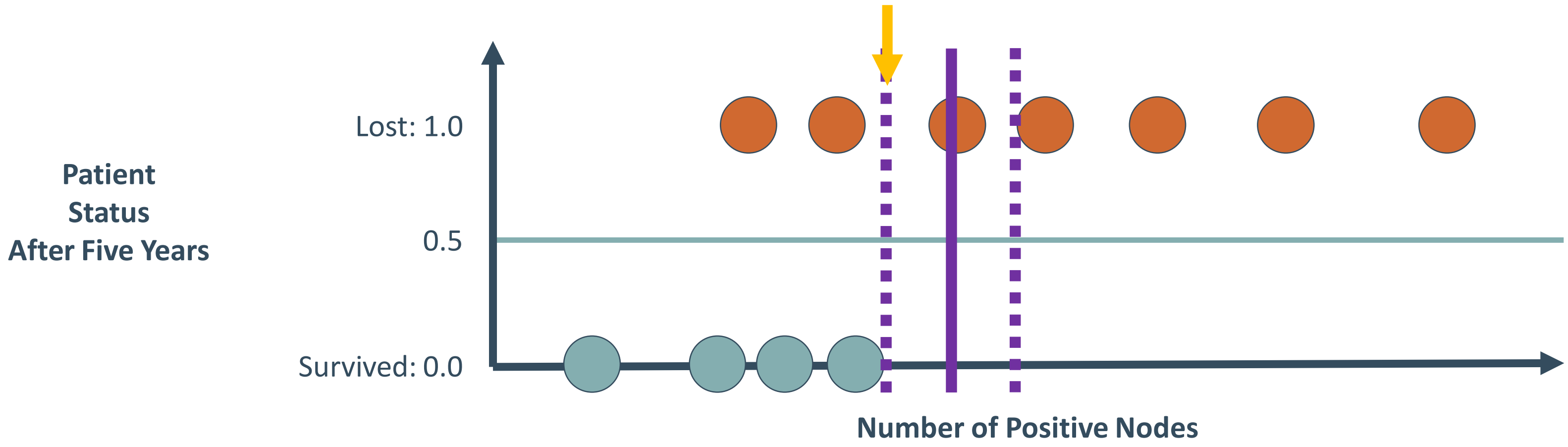

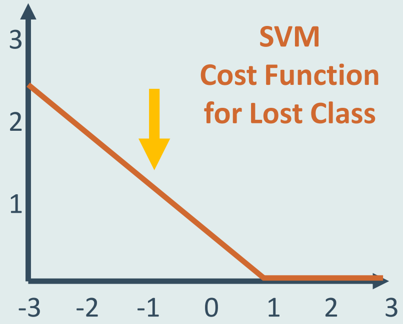

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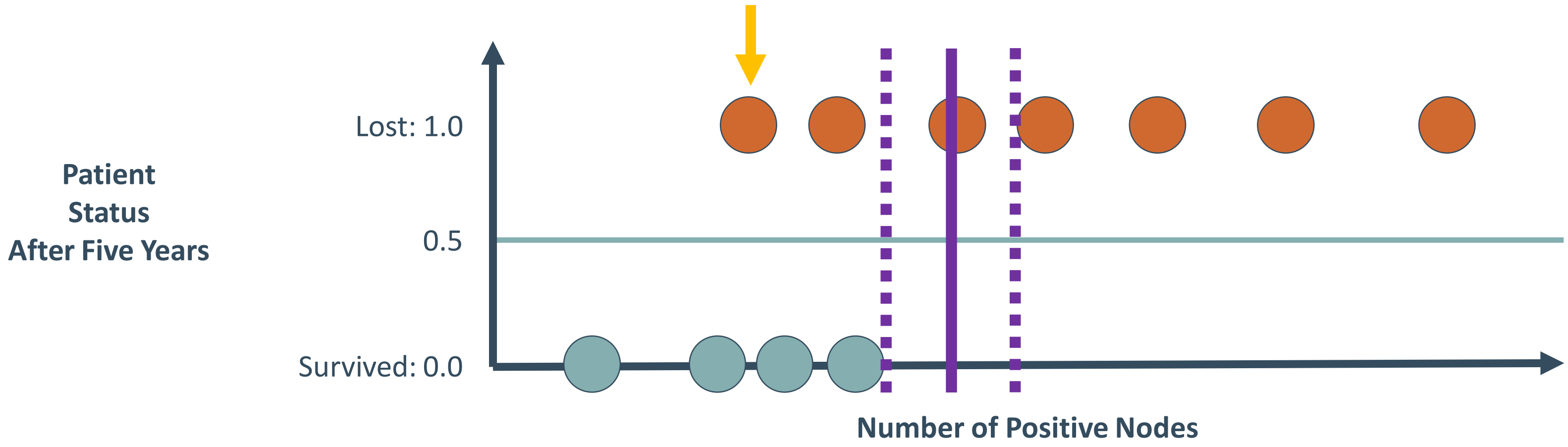
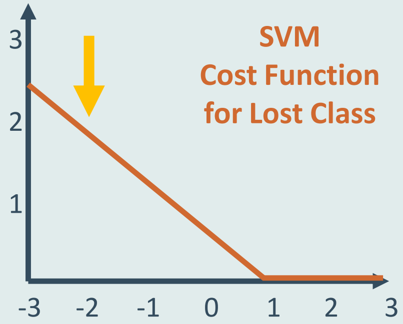
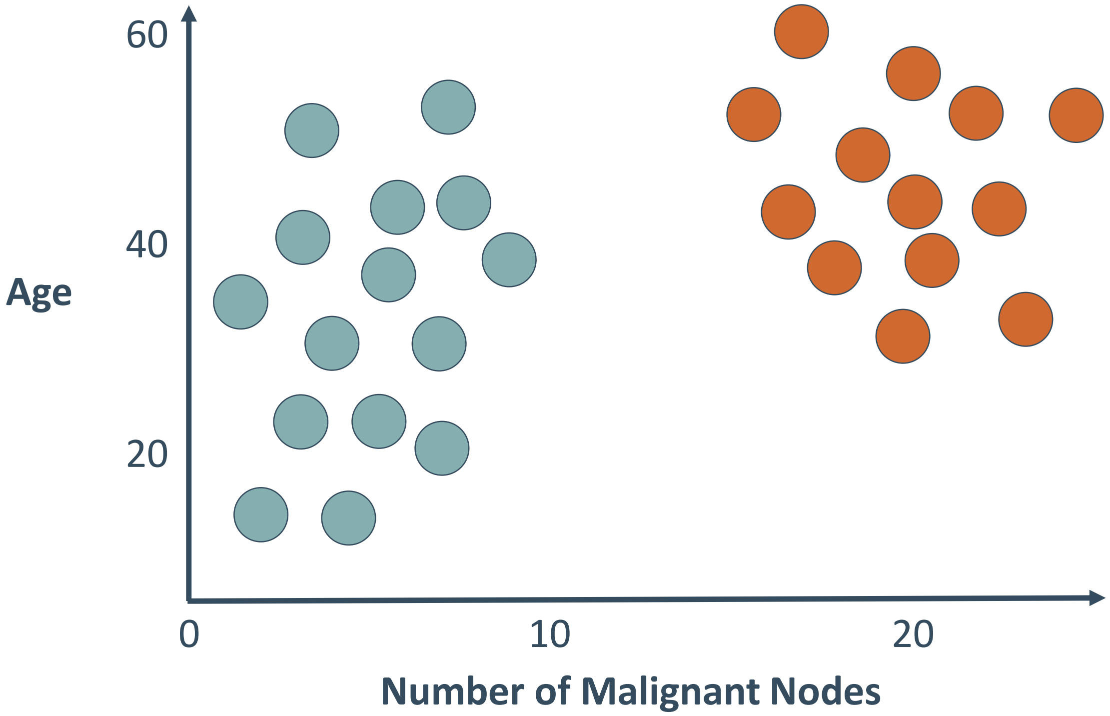




Outlier Sensitivity in SVMs



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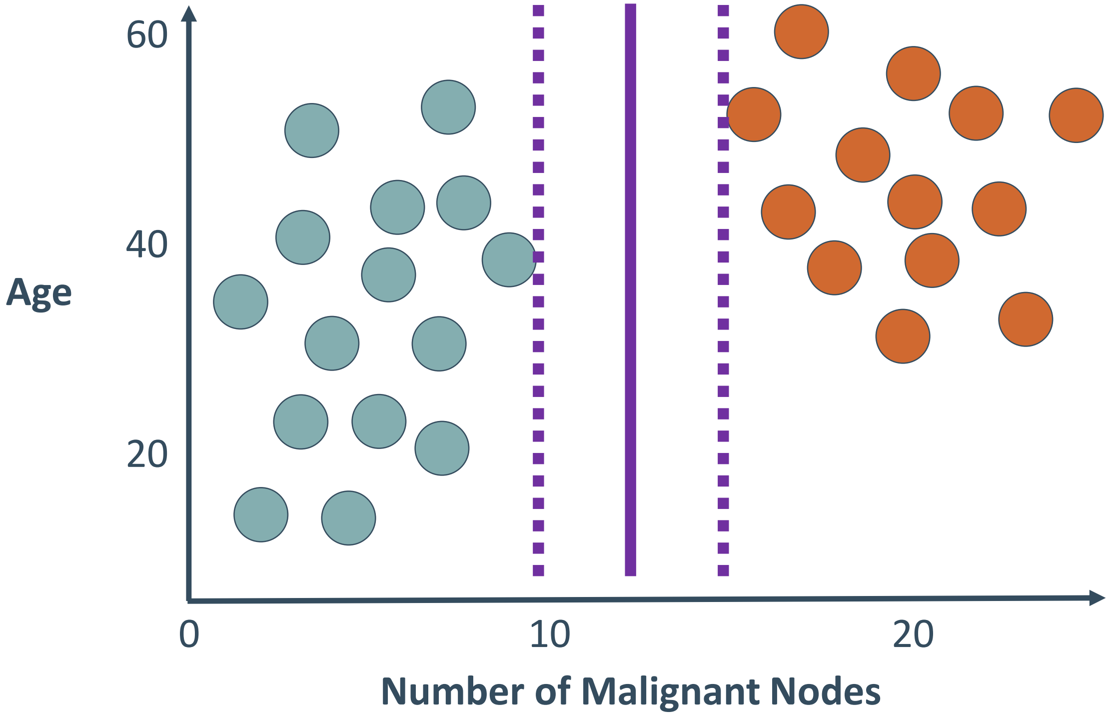

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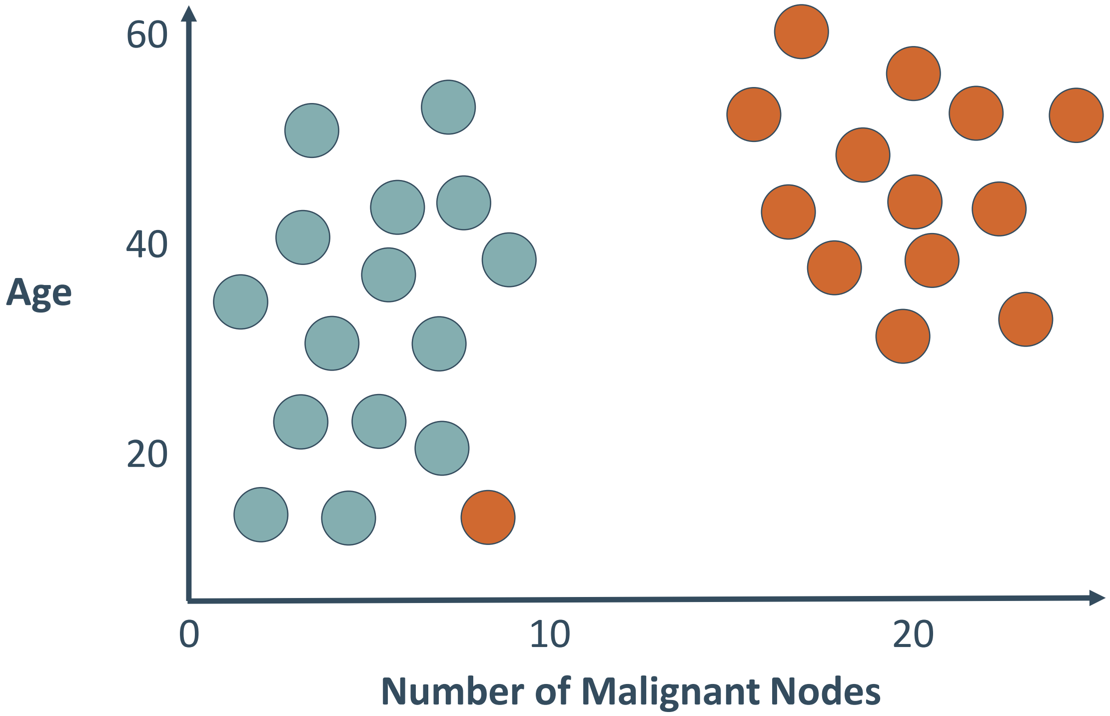

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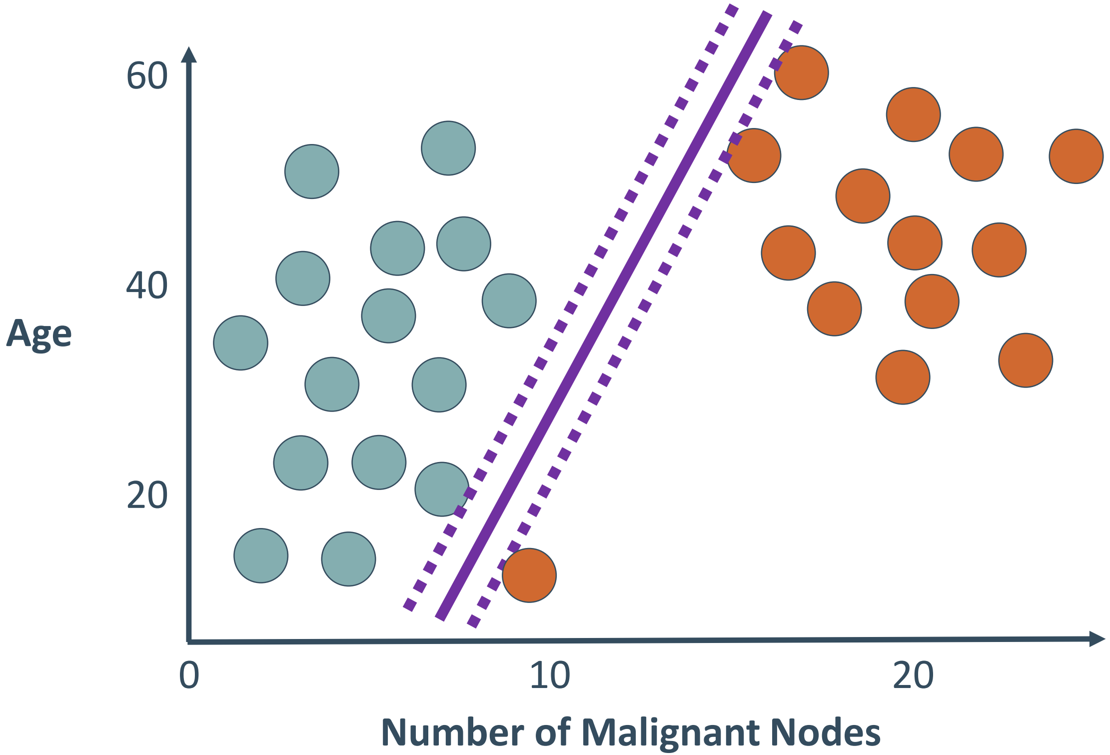
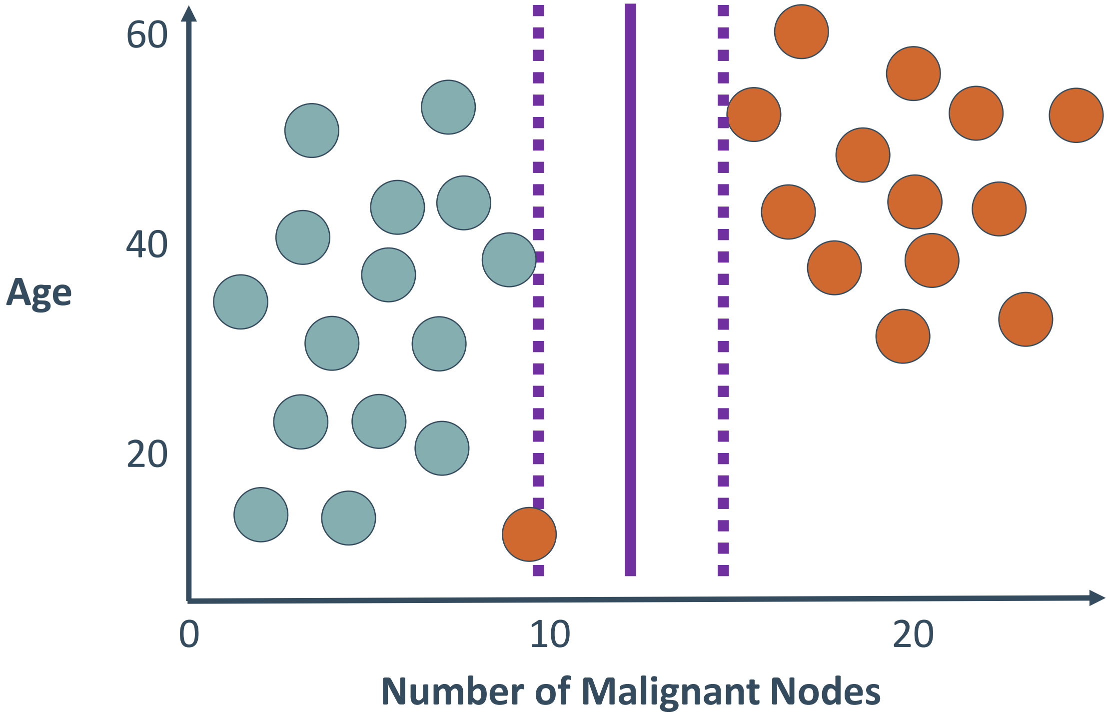


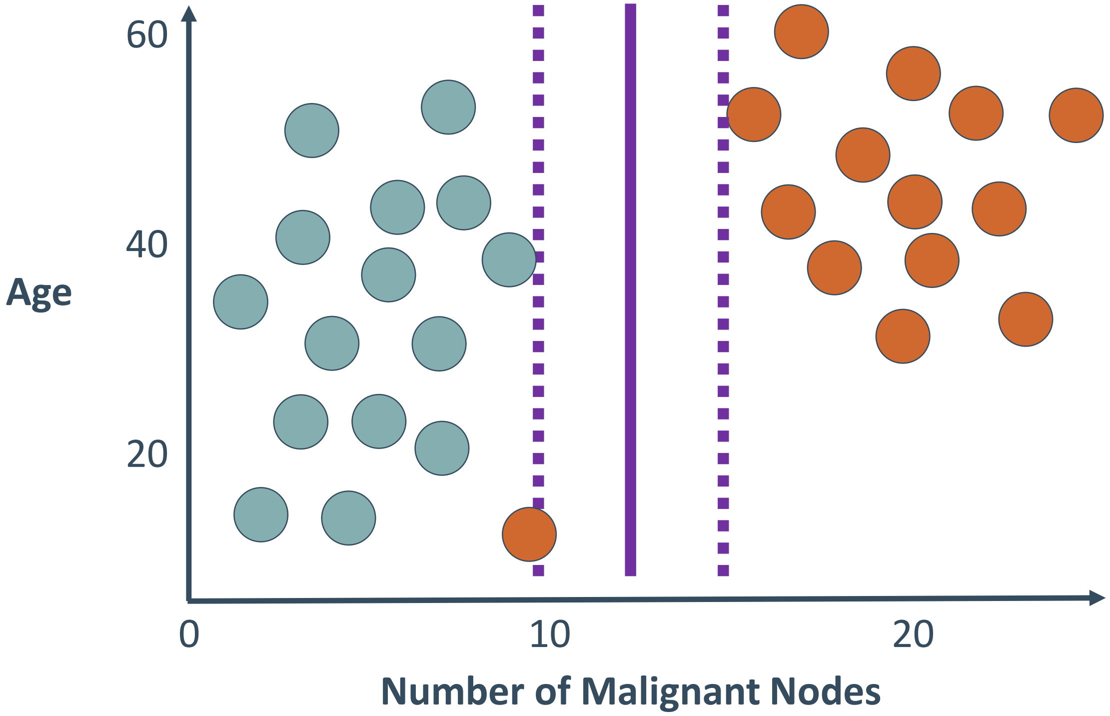
Outlier Sensitivity in SVMs

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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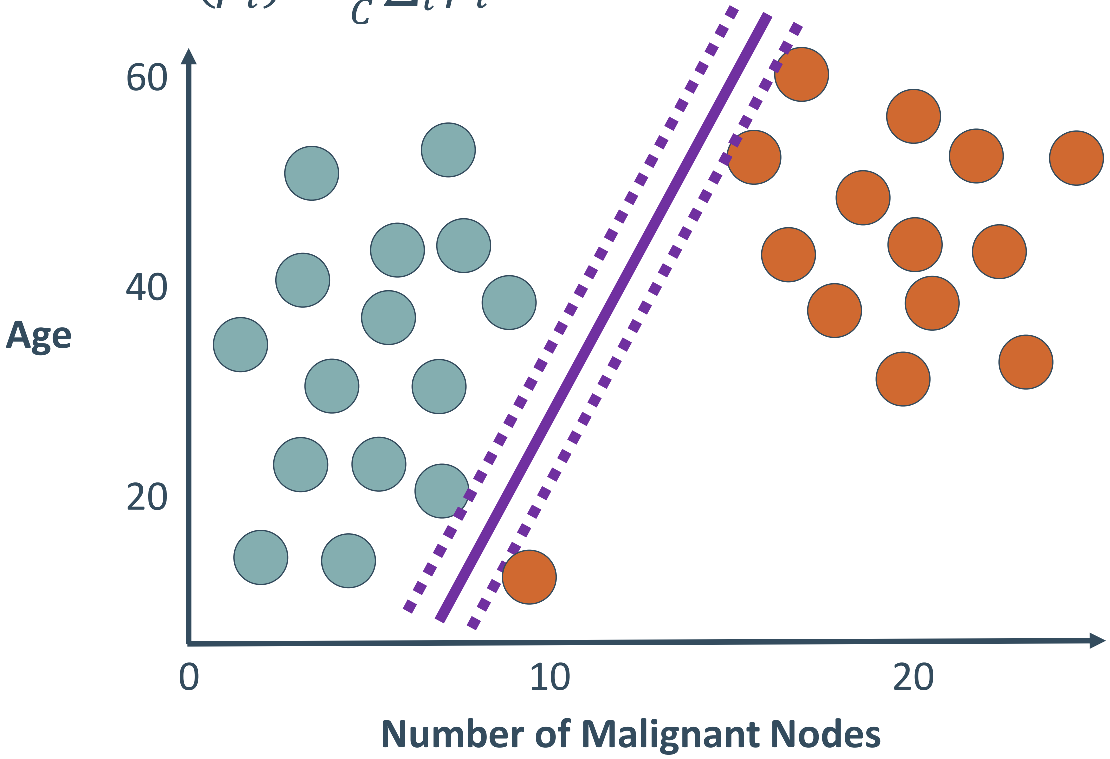

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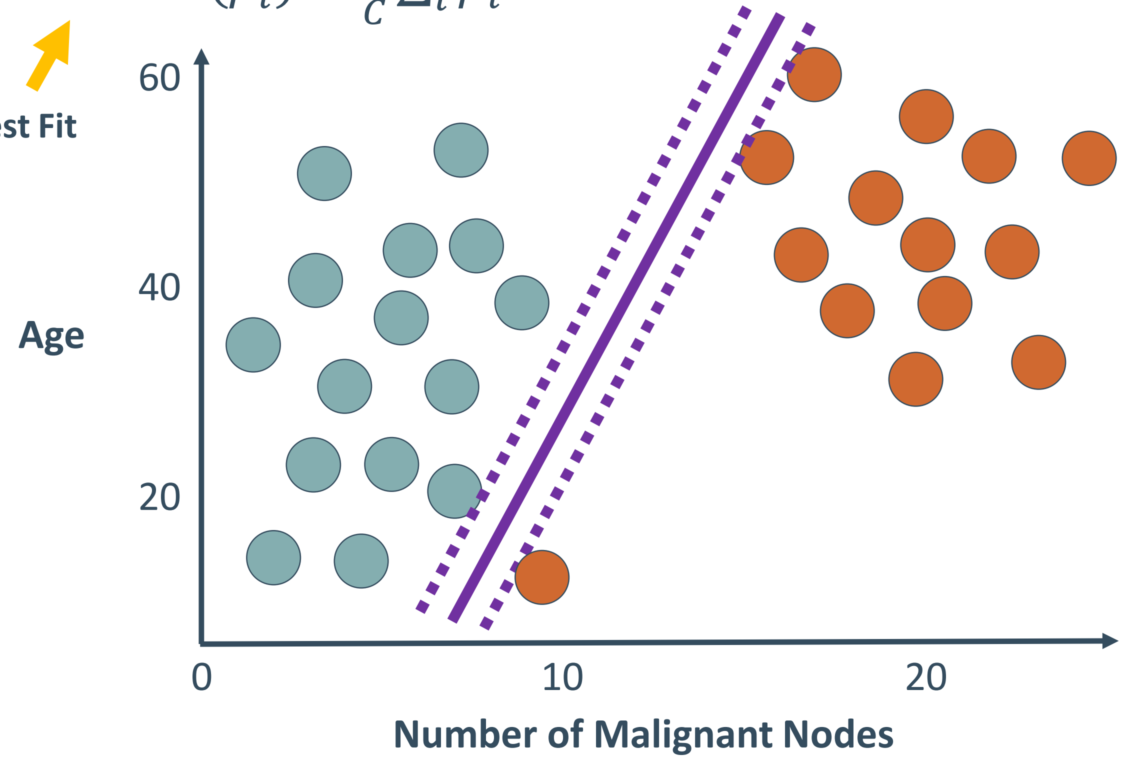
Best Fit



Regularization in SVMs

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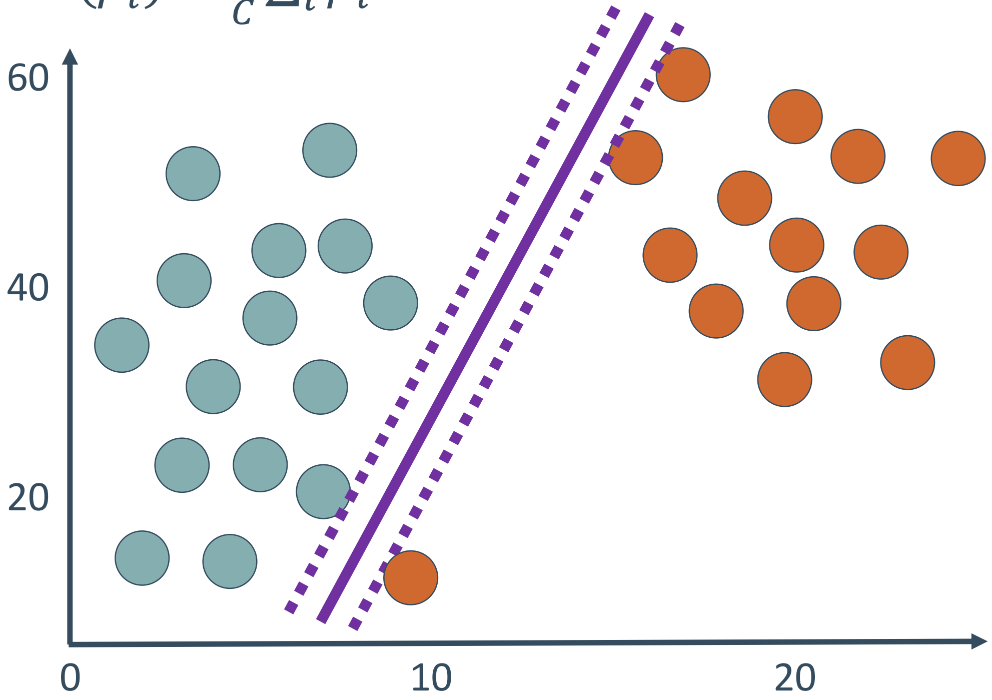
Large

Best Fit



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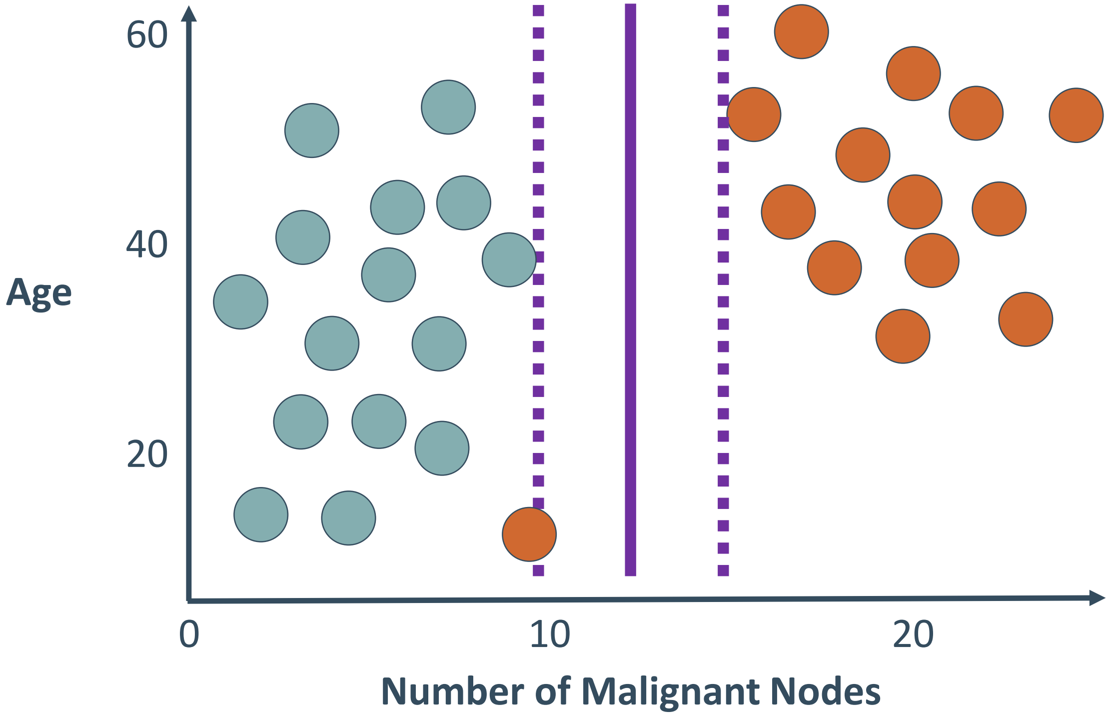

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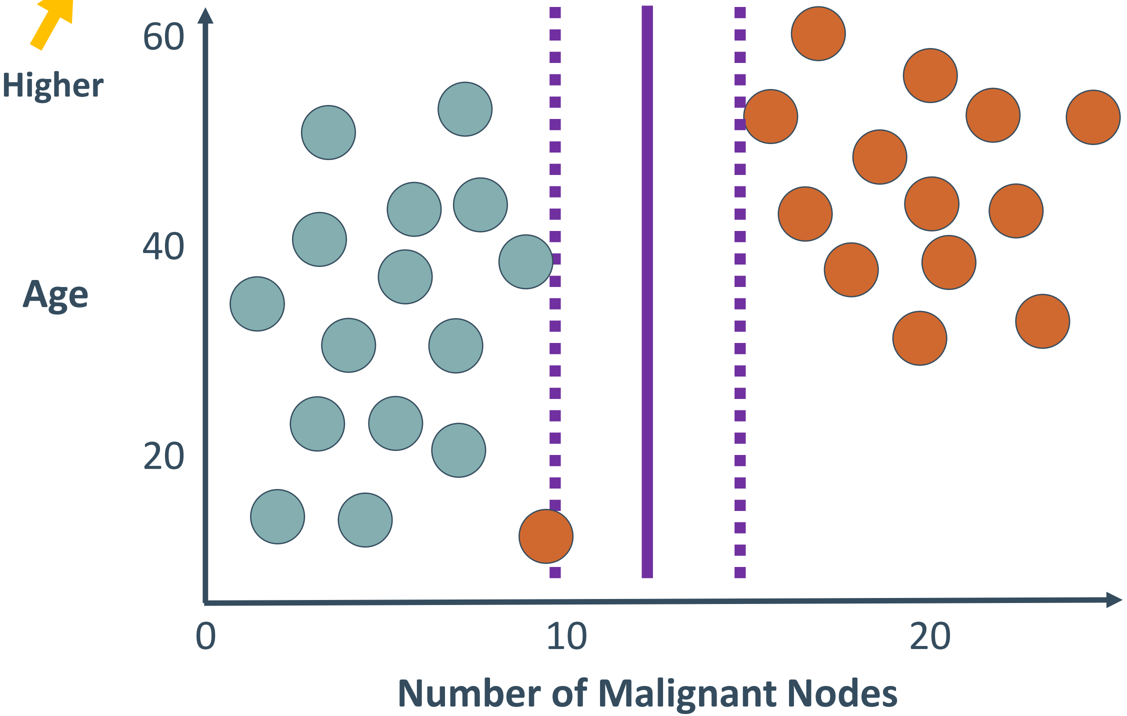
Slightly Higher



Regularization in SVMs

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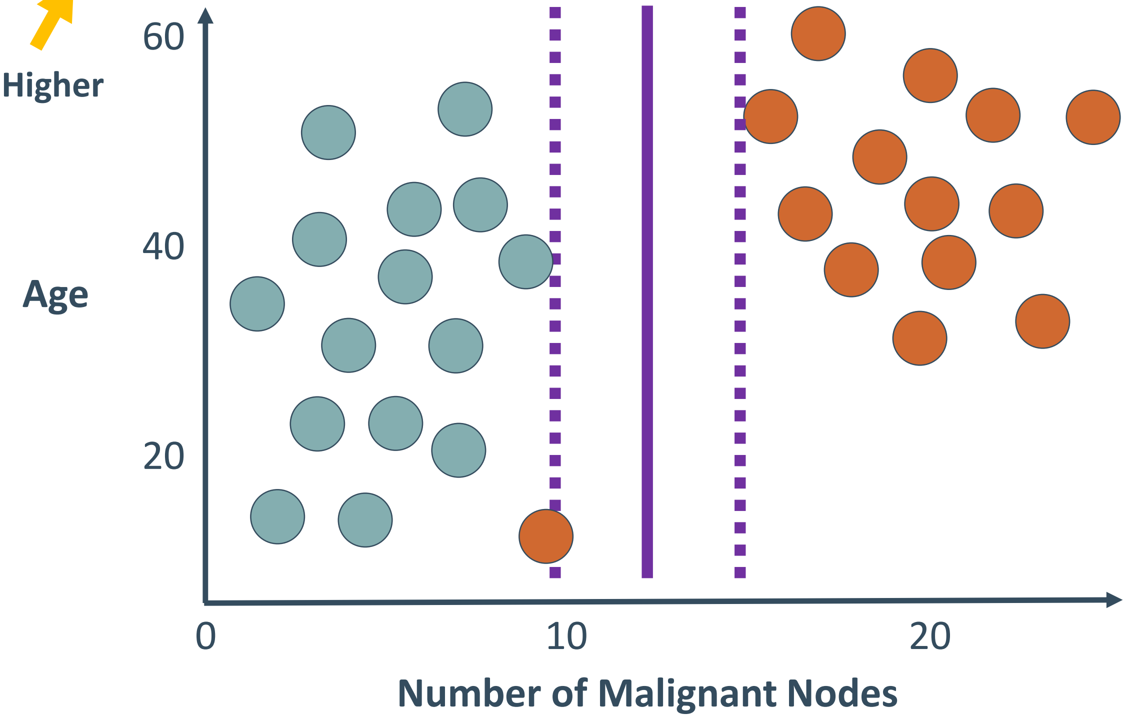
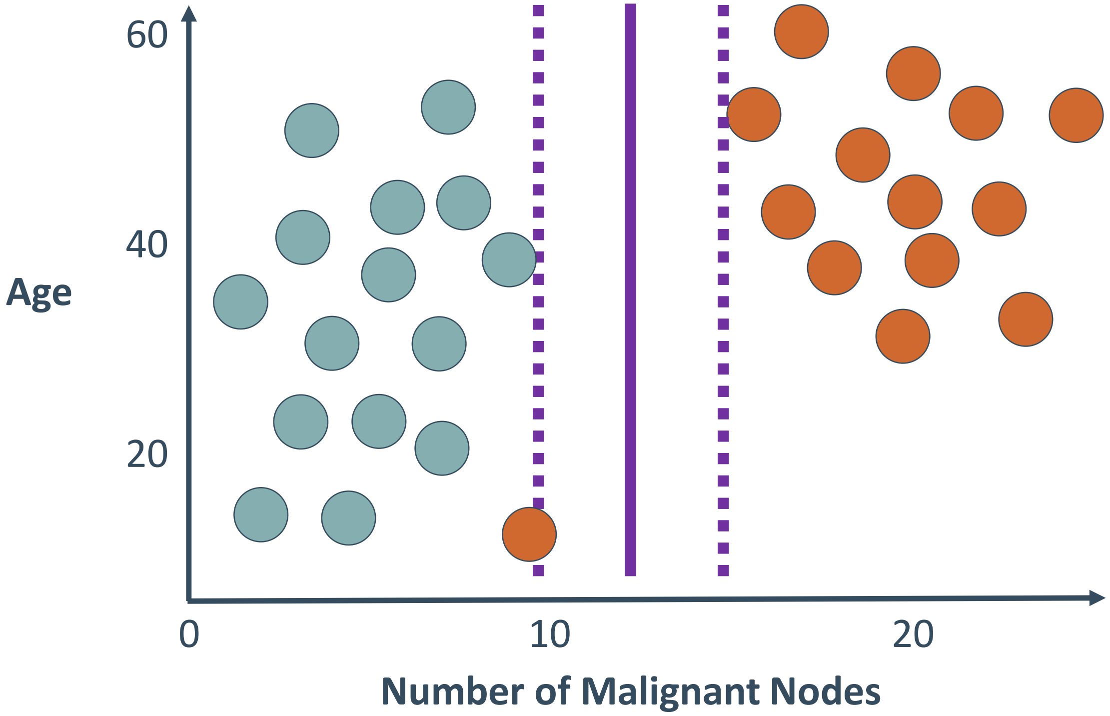
Much Smaller

Slightly Higher



Interpretation of SVM Coefficients

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



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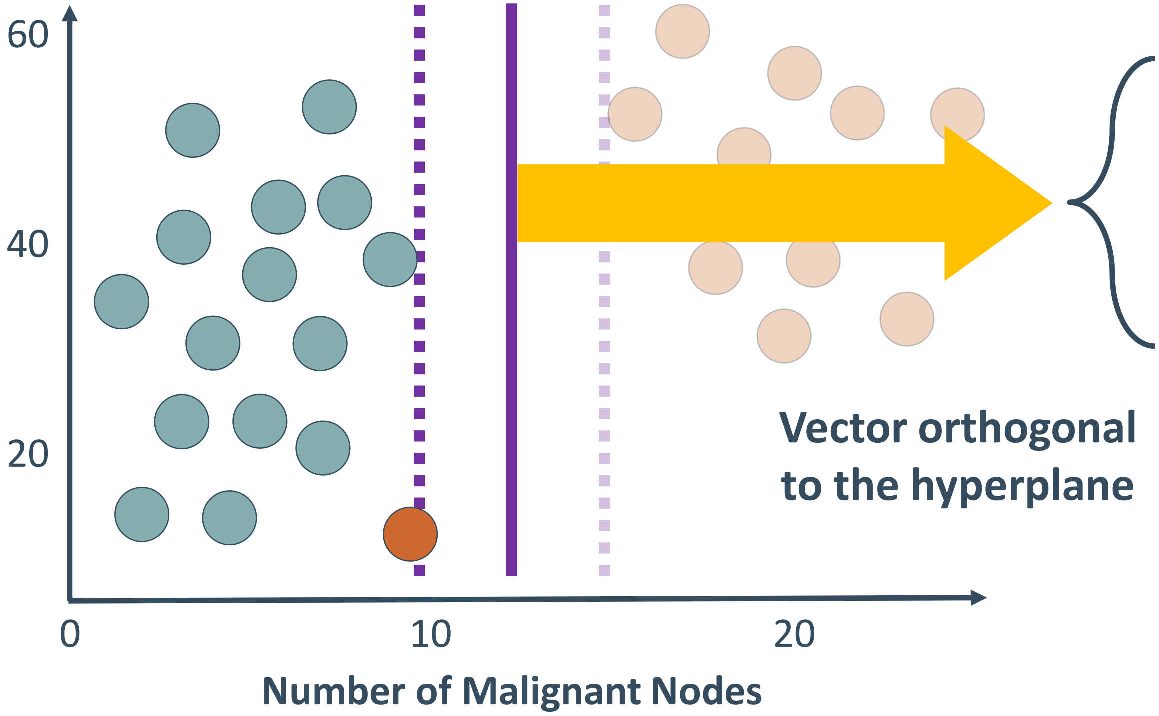

$$\left\{\begin{bmatrix}\beta_1\\ \beta_2\\ \beta_3\end{bmatrix}\right.$$

Linear SVM: The Syntax

Import the class containing the classification method.

```
from sklearn.svm import LinearSVC
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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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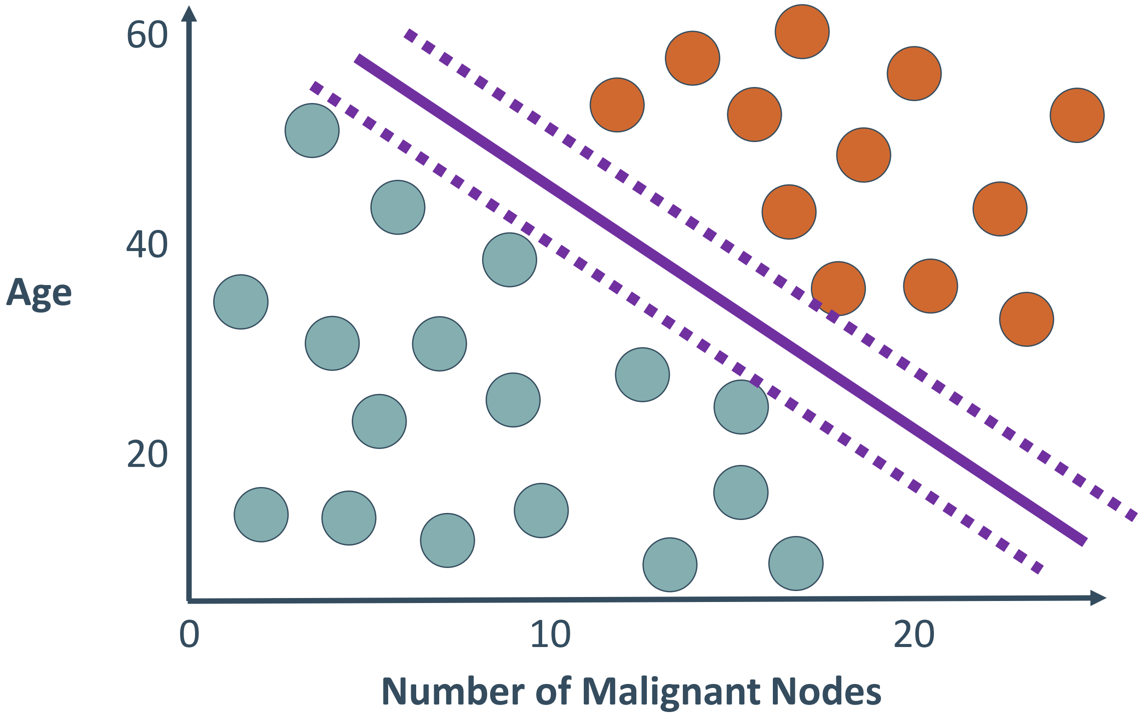
Tune regularization parameters with cross-validation.

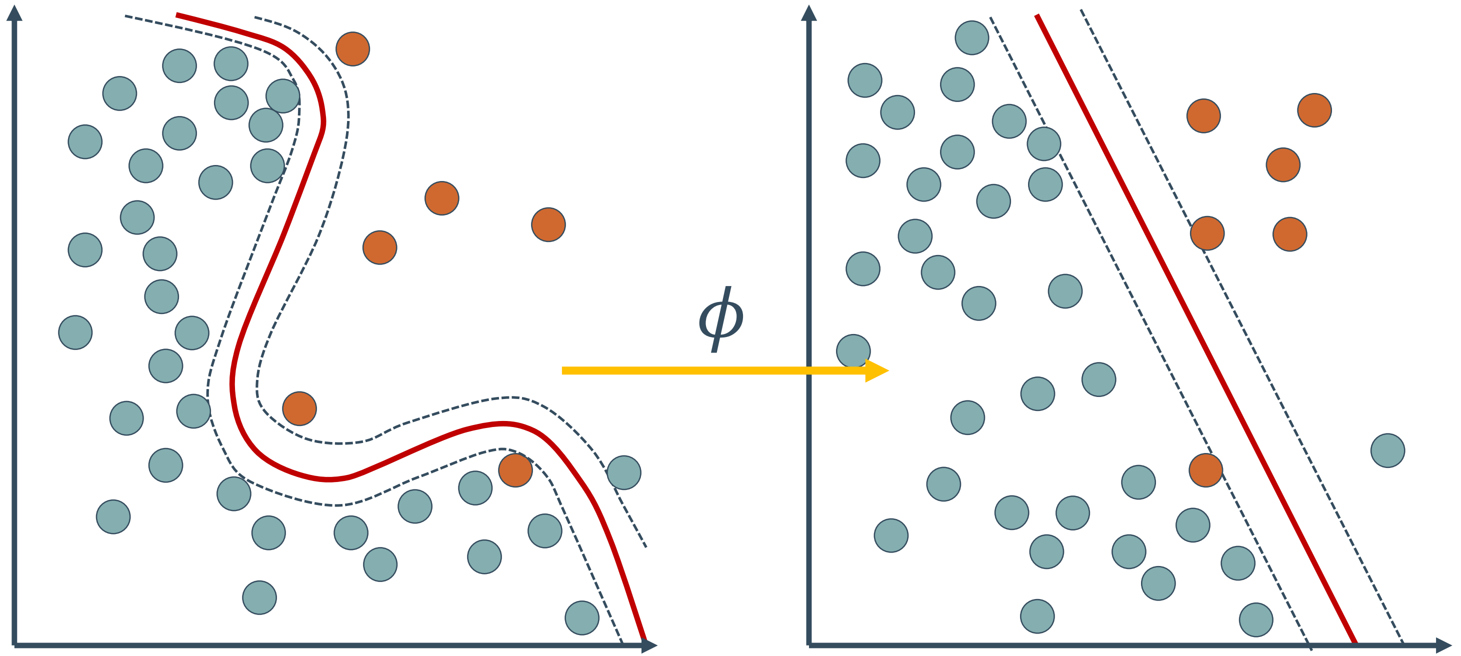
Kernels

Classification with SVMs



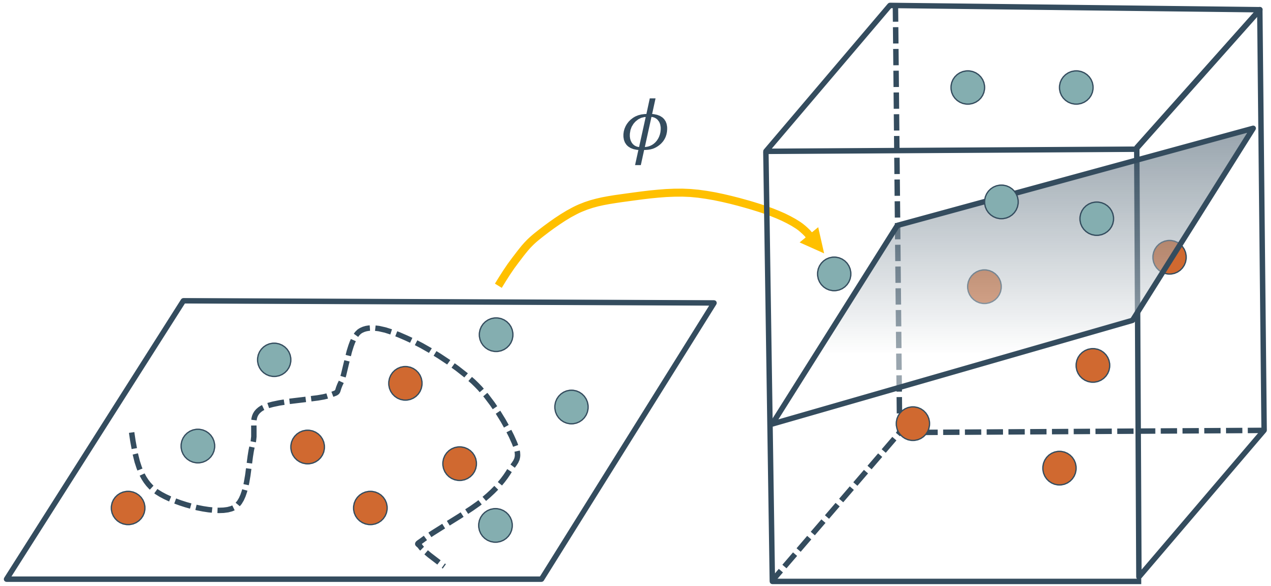
Non-Linear Decision Boundaries with SVM

Non-linear data can be made linear with higher dimensionality.



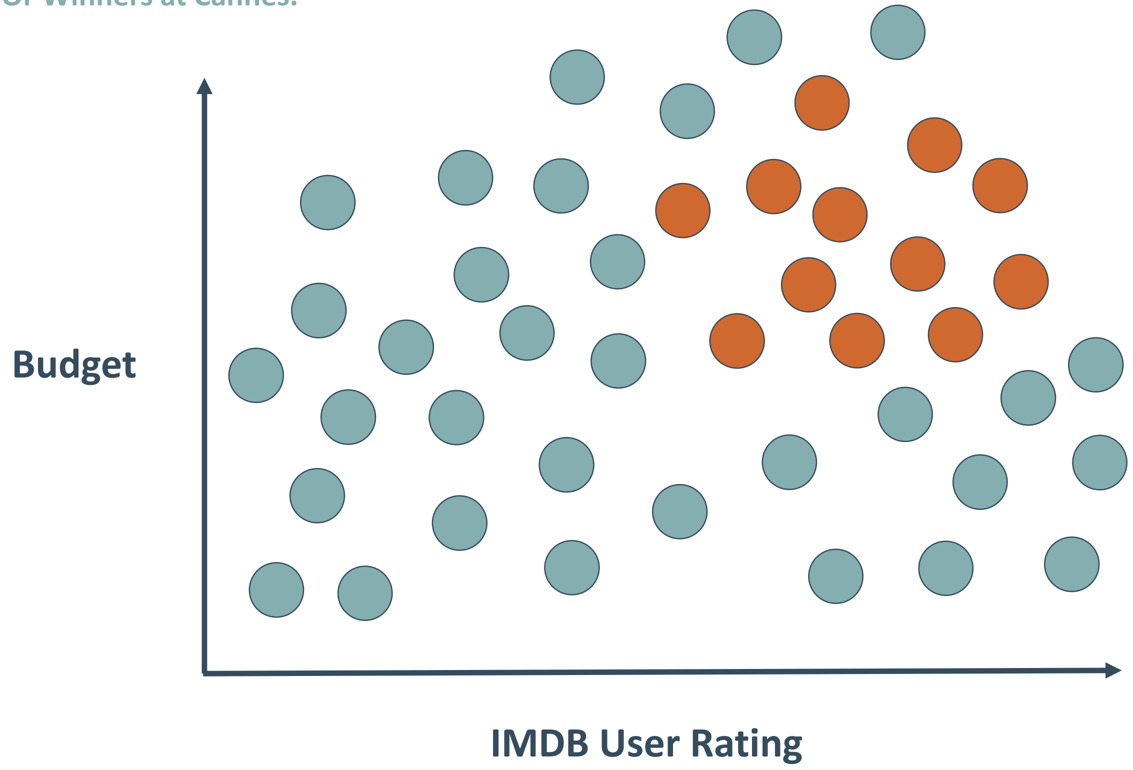
The Kernel Trick

Transform data so it is linearly separable.



SVM Gaussian Kernel

Palme d'Or Winners at Cannes.



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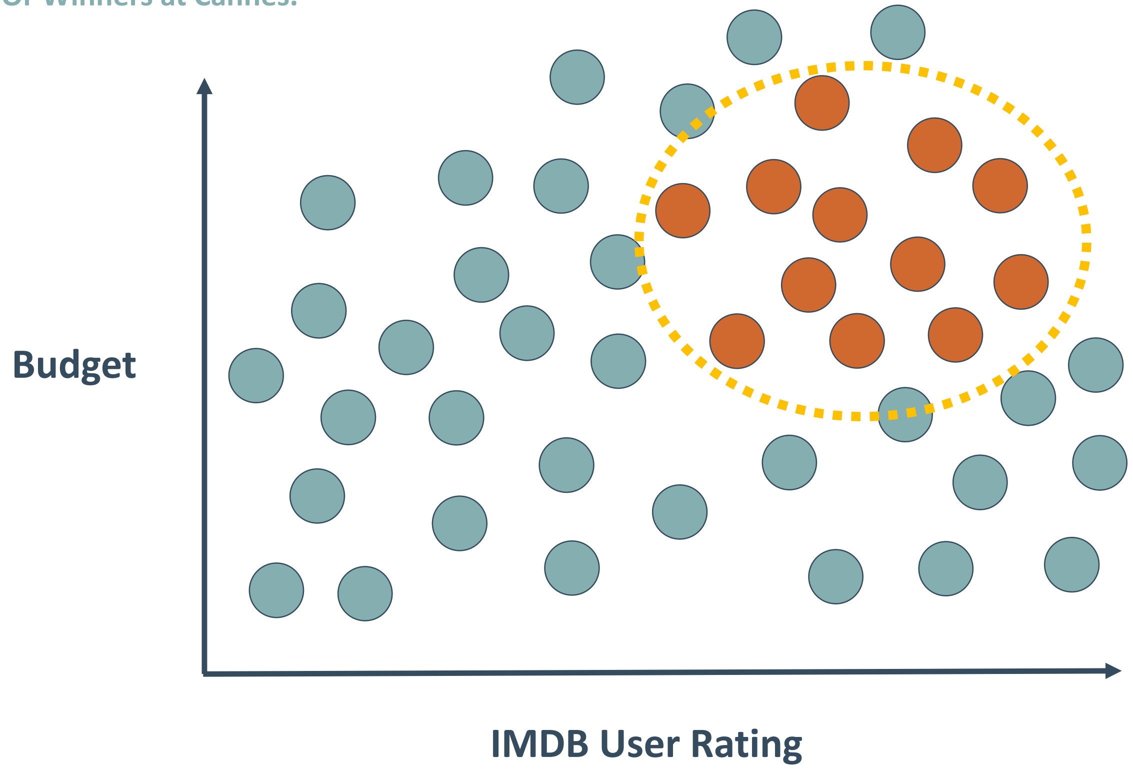
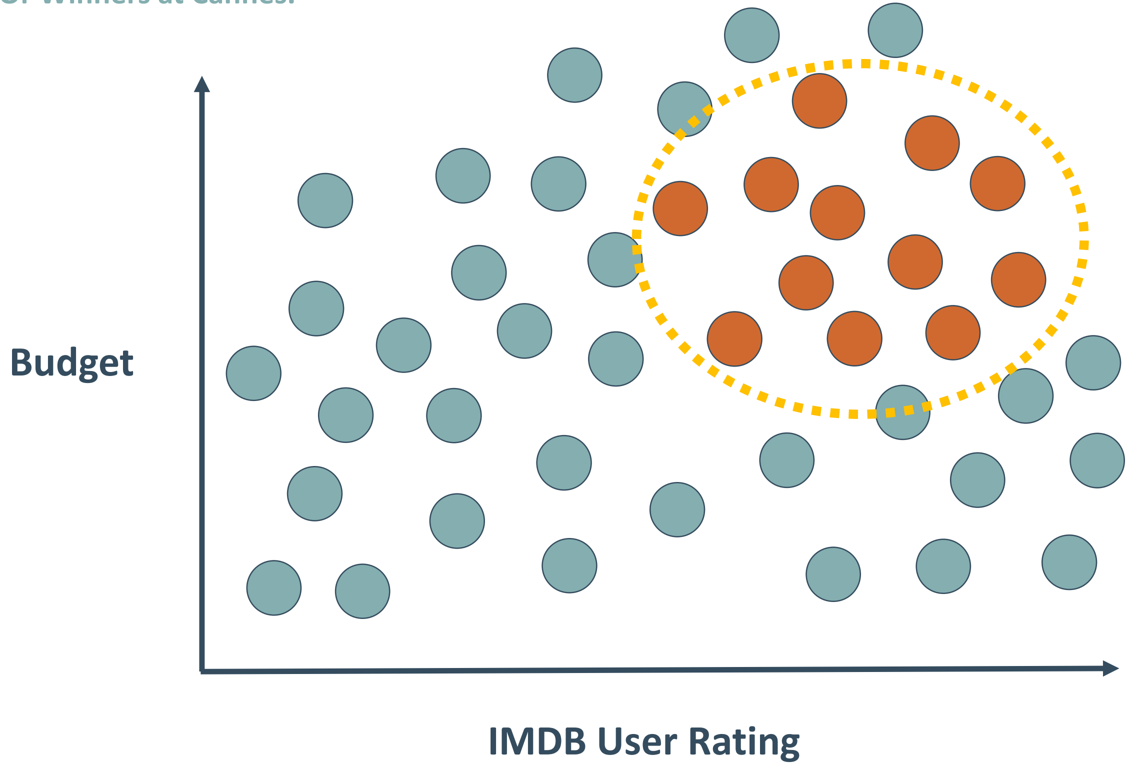


Approach 1:
Create higher order features to transform the data.

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

SVM Gaussian Kernel

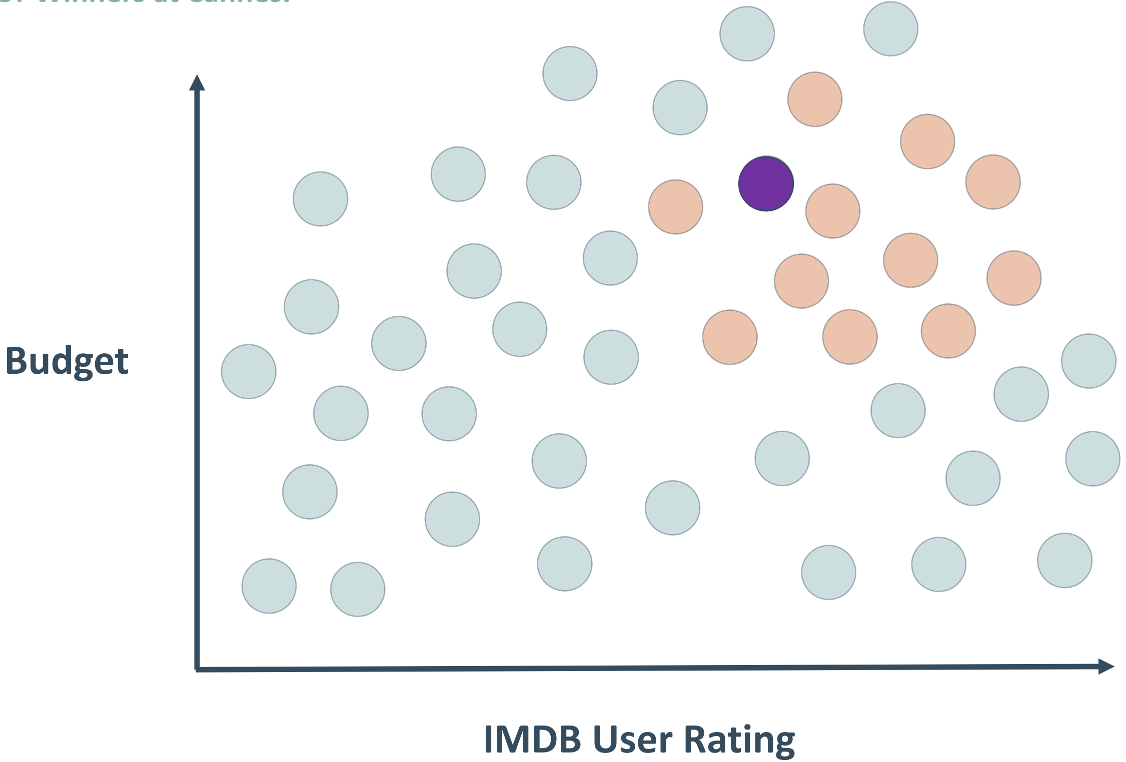
Palme d'Or Winners at Cannes.



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

SVM Gaussian Kernel

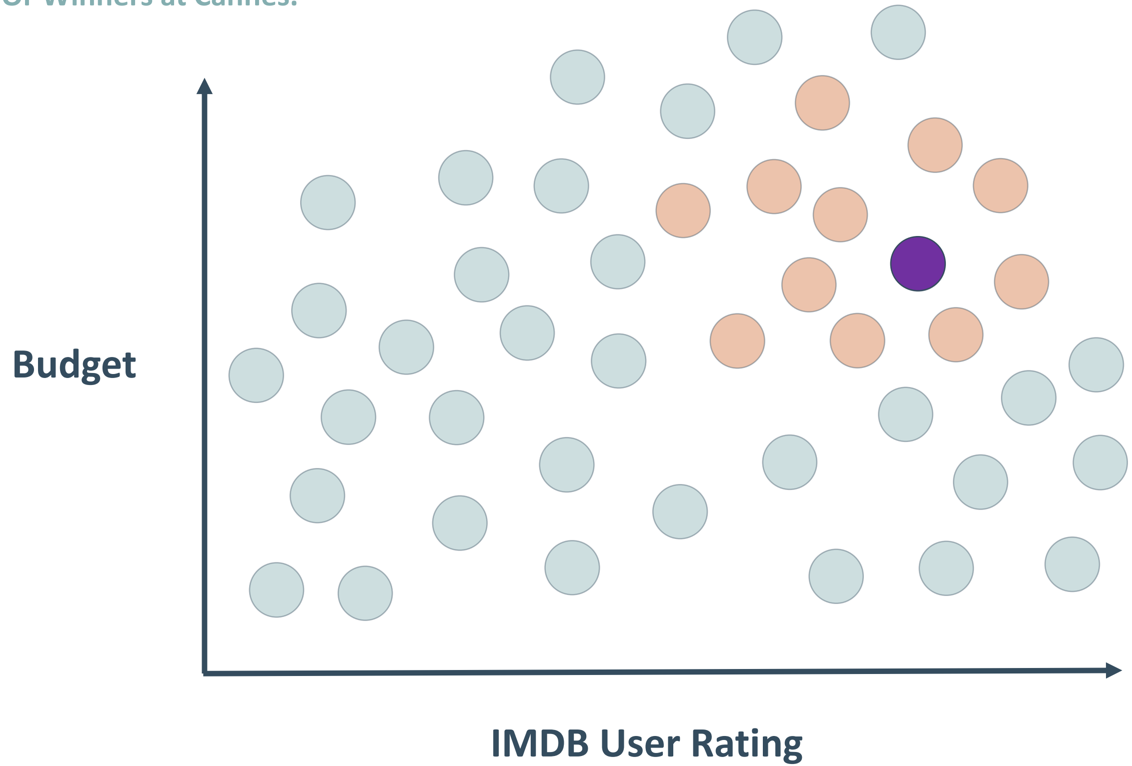
Palme d'Or Winners at Cannes.



Define Feature 1:
Similarity to
"Pulp Fiction."

SVM Gaussian Kernel

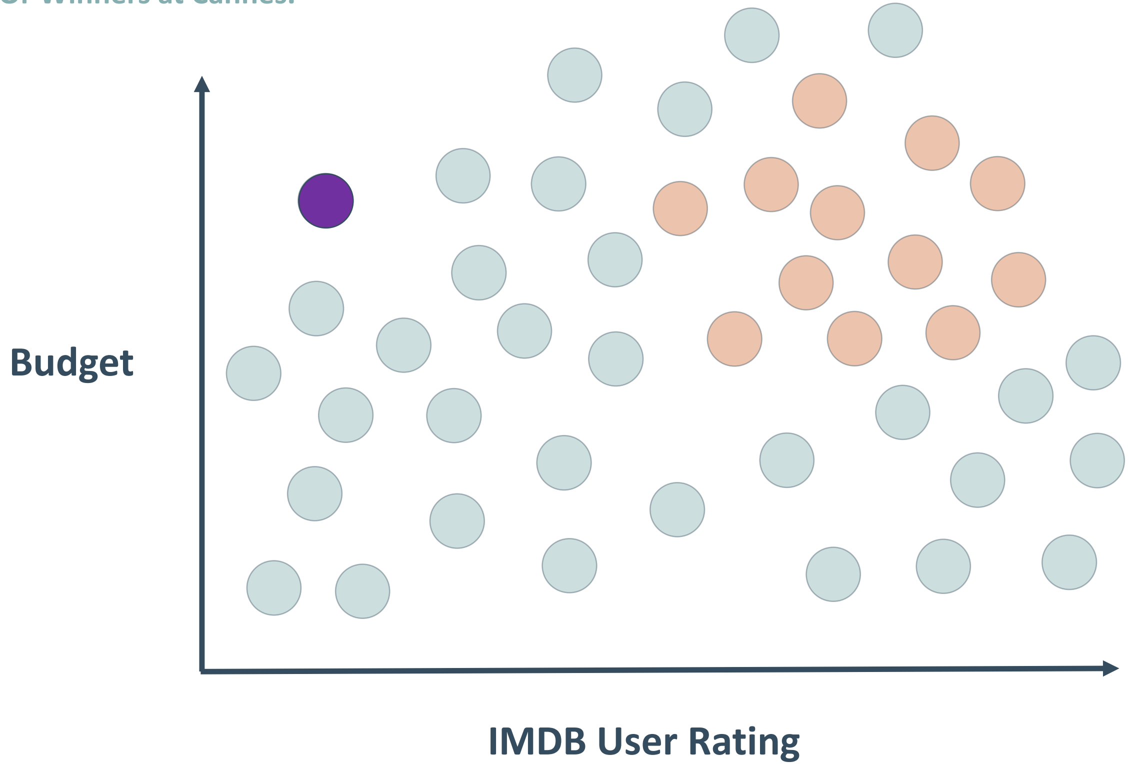
Palme d'Or Winners at Cannes.



Define Feature 2:
Similarity to
"Black Swan."

SVM Gaussian Kernel

Palme d'Or Winners at Cannes.



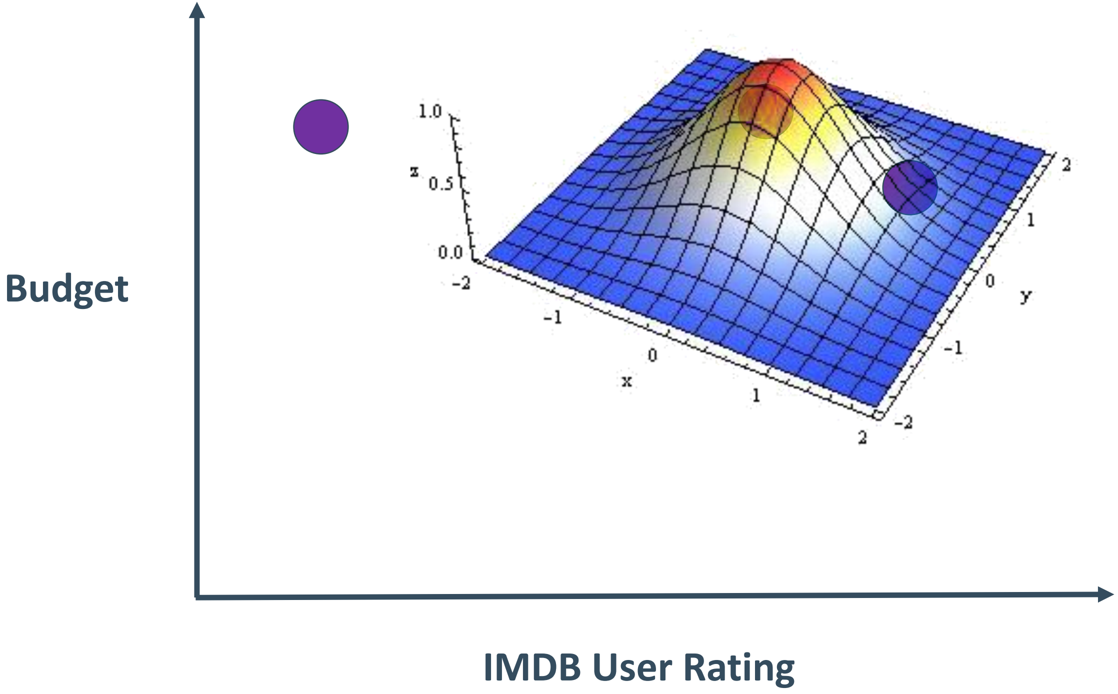
Define Feature 3:
Similarity to "Transformers."

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.



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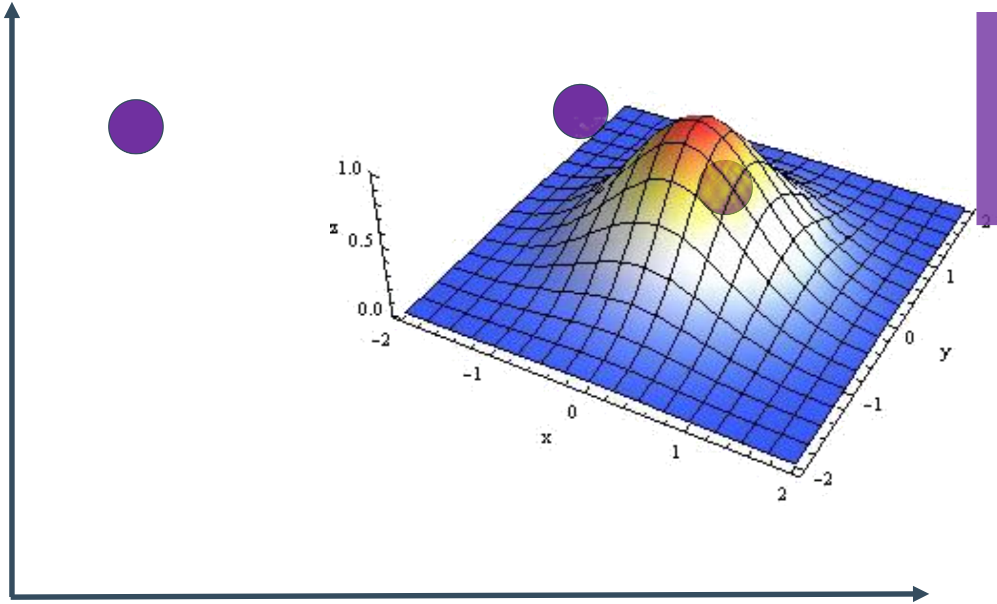
Create a Gaussian function at feature 2.

Budget



IMDB User Rating

SVM Gaussian Kernel

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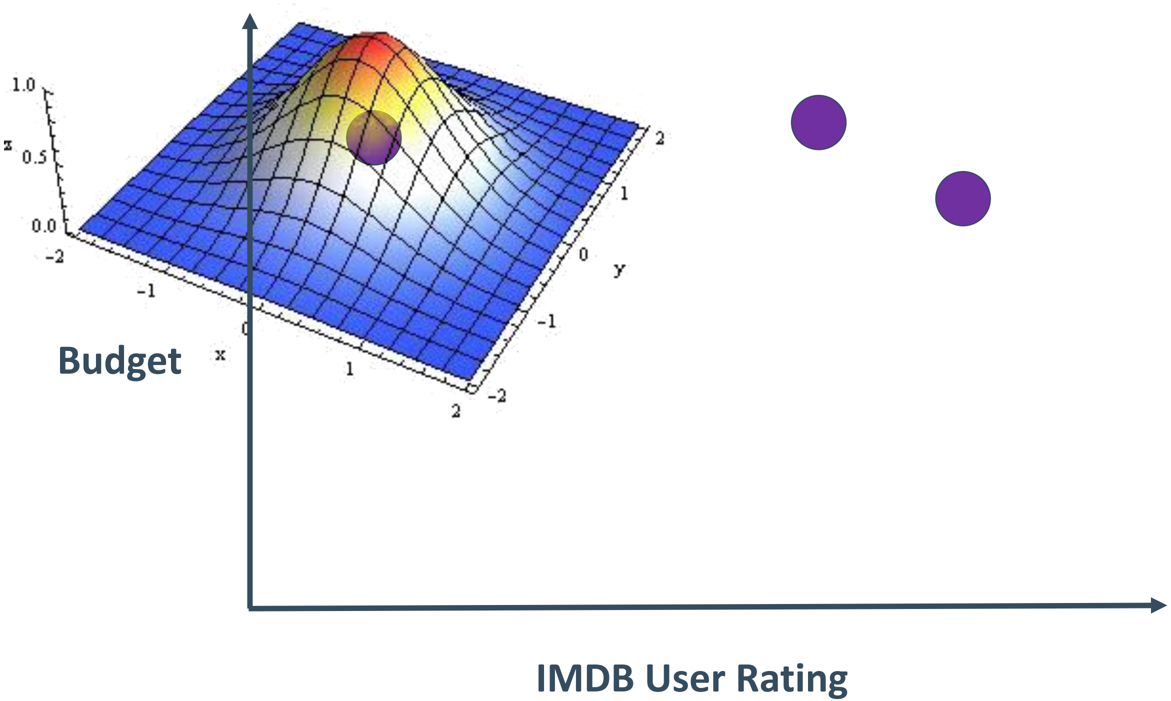
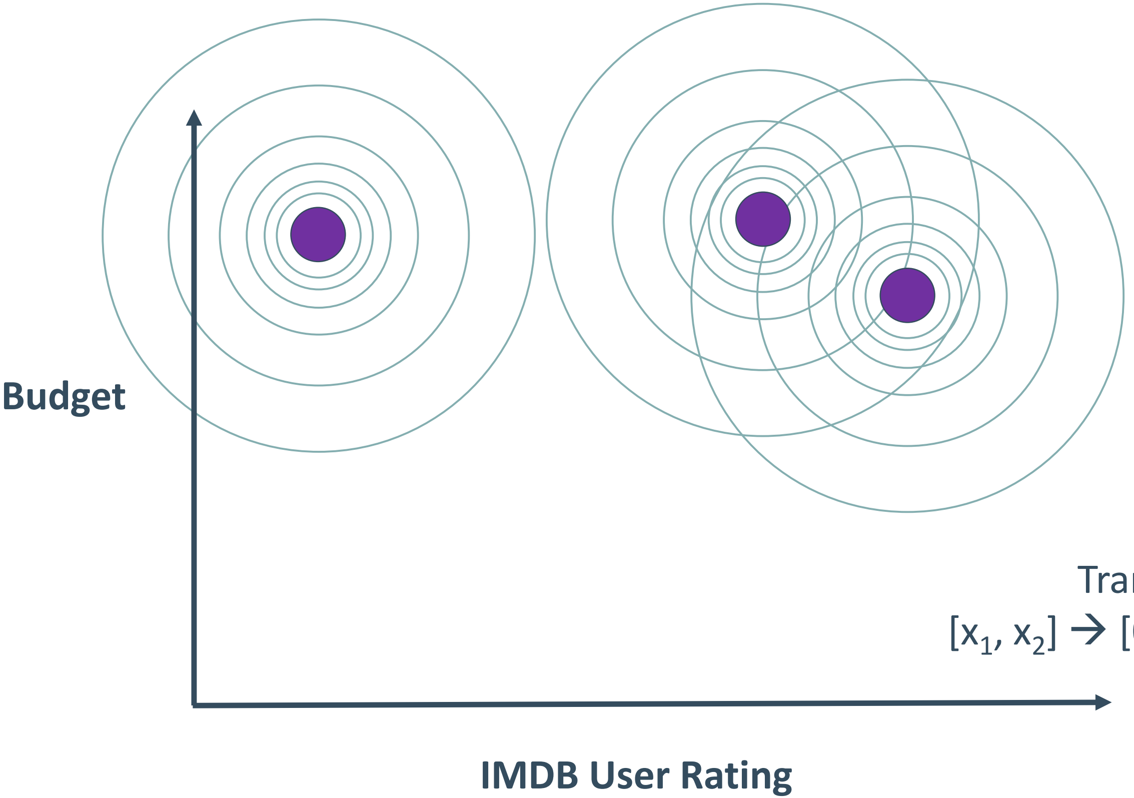


Create a Gaussian function at feature 3.

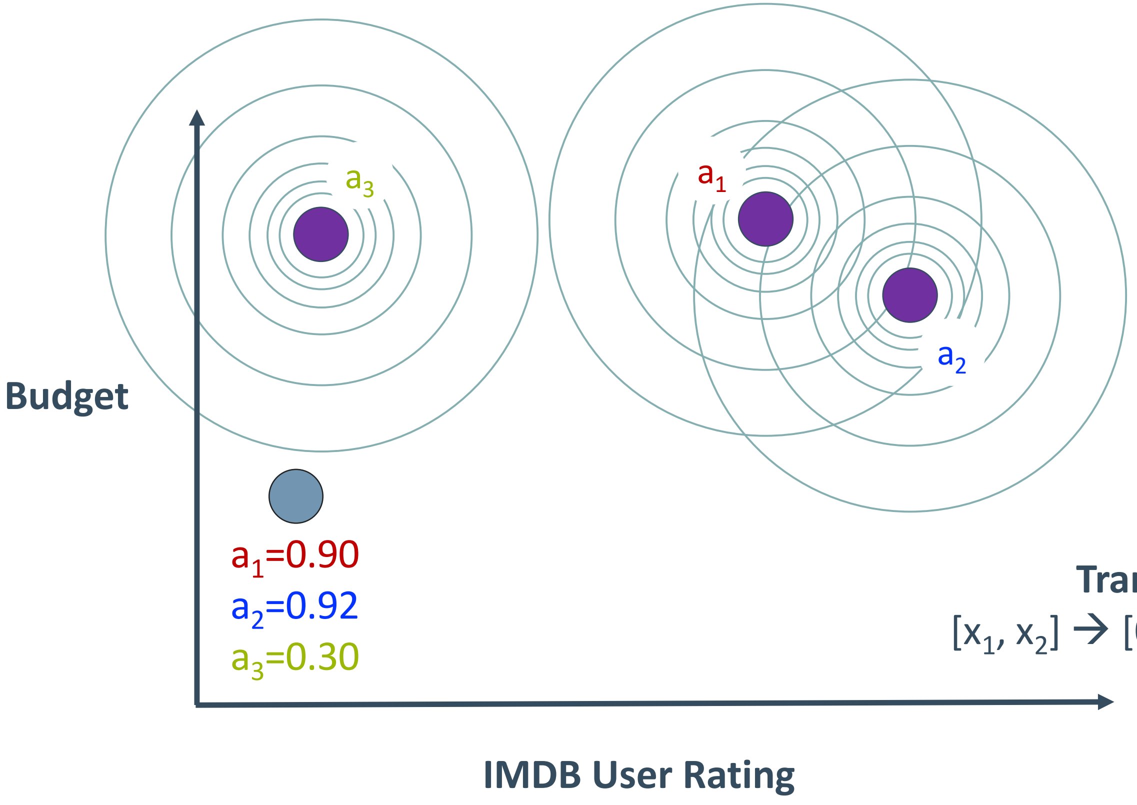
SVM Gaussian Kernel



Transformation:

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

SVM Gaussian Kernel



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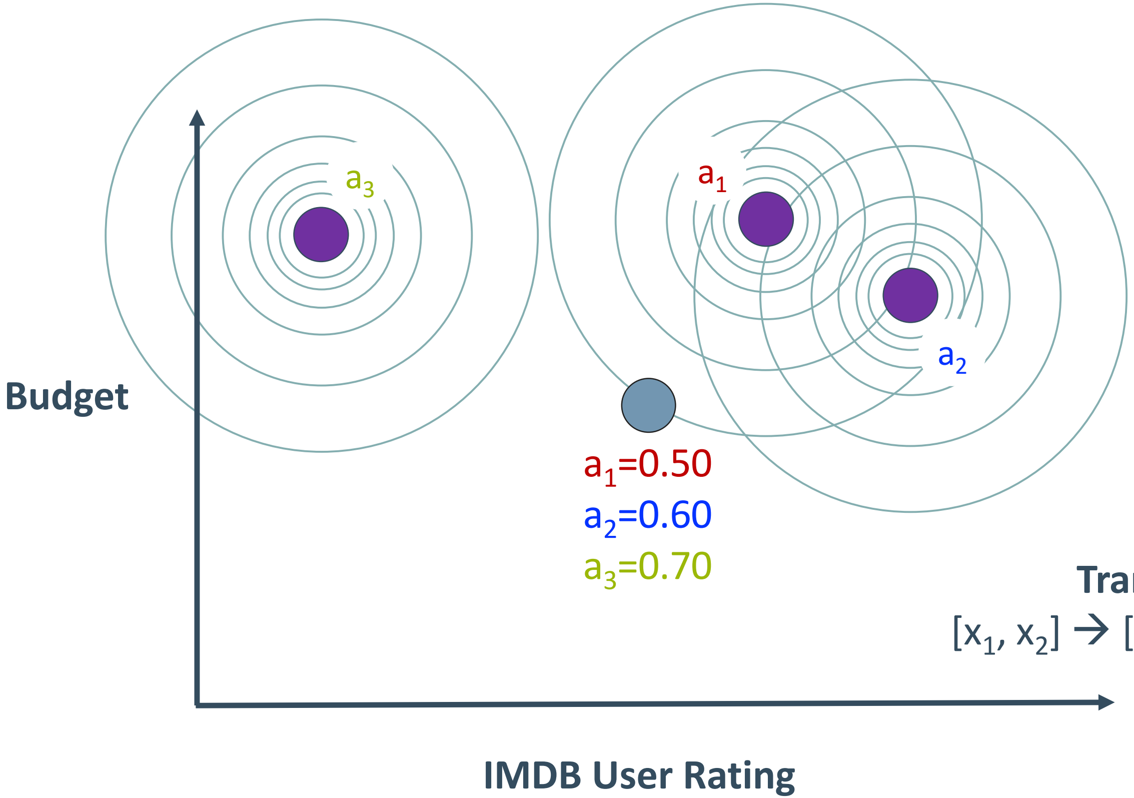

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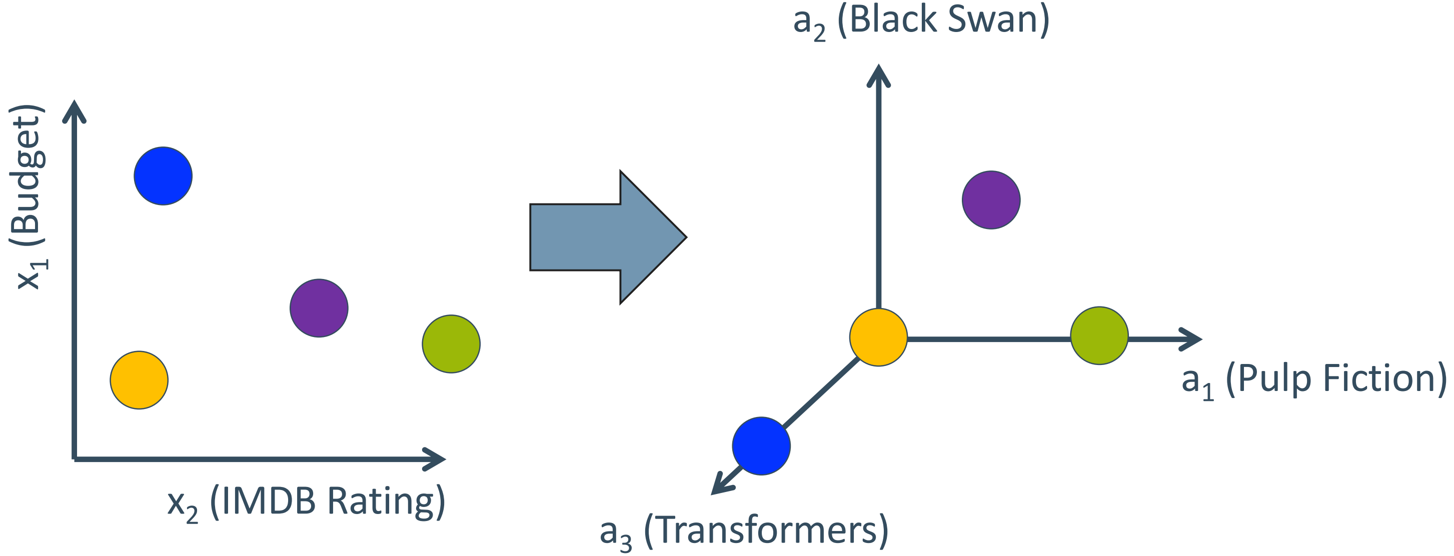
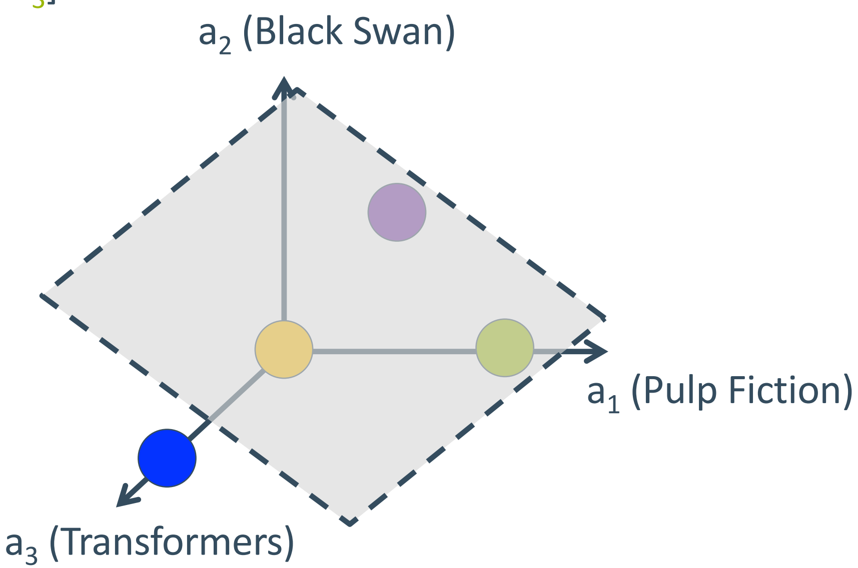


Classification in the New Space

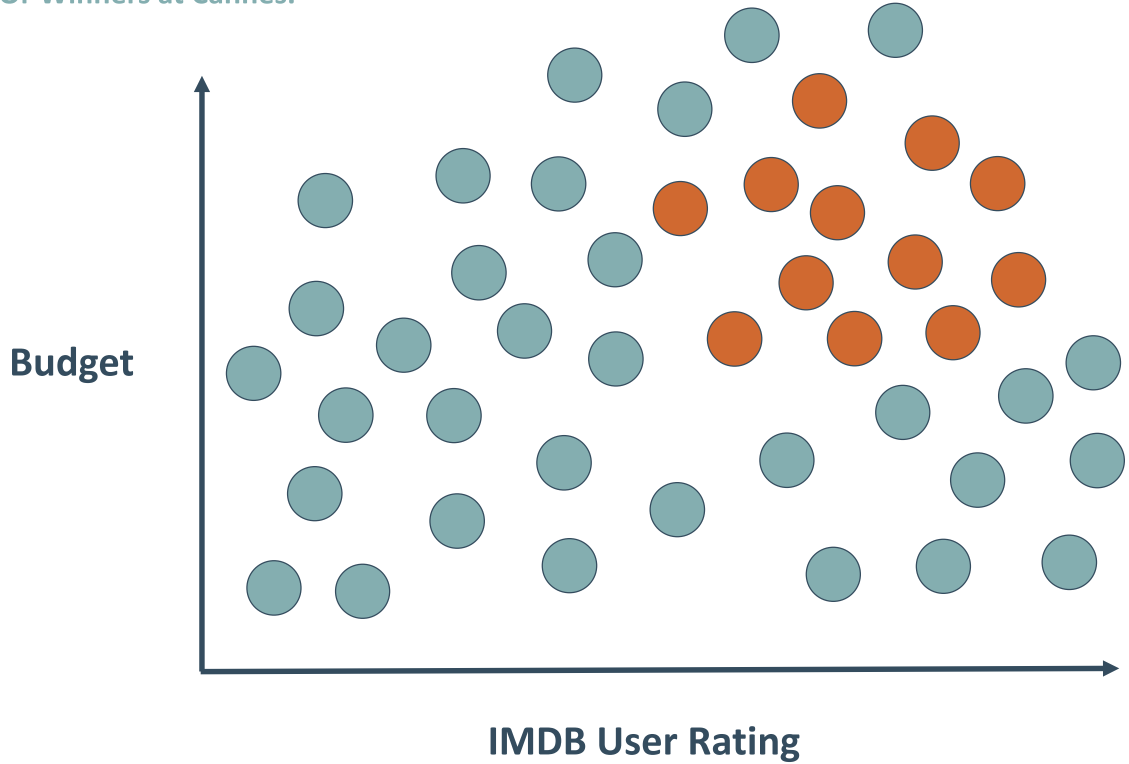
Transformation:

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



SVM Gaussian Kernel

Palme d'Or Winners at Cannes.



SVM Gaussian Kernel

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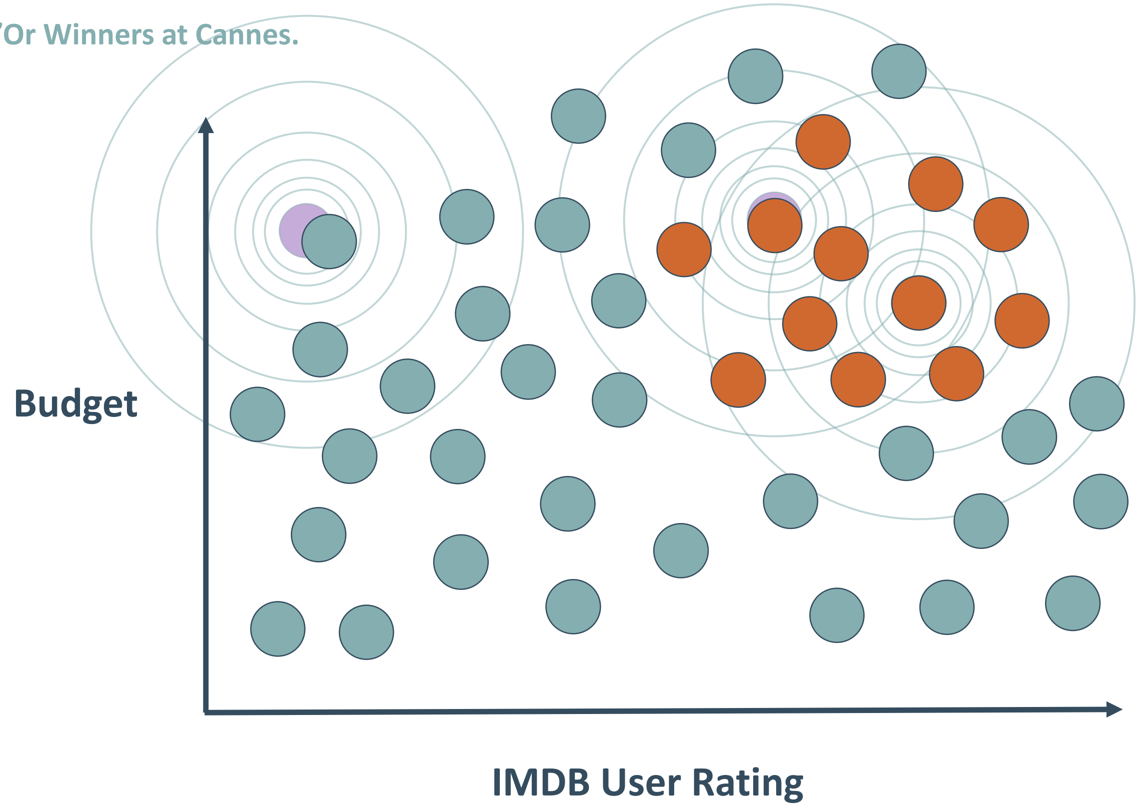

SVM Gaussian Kernel

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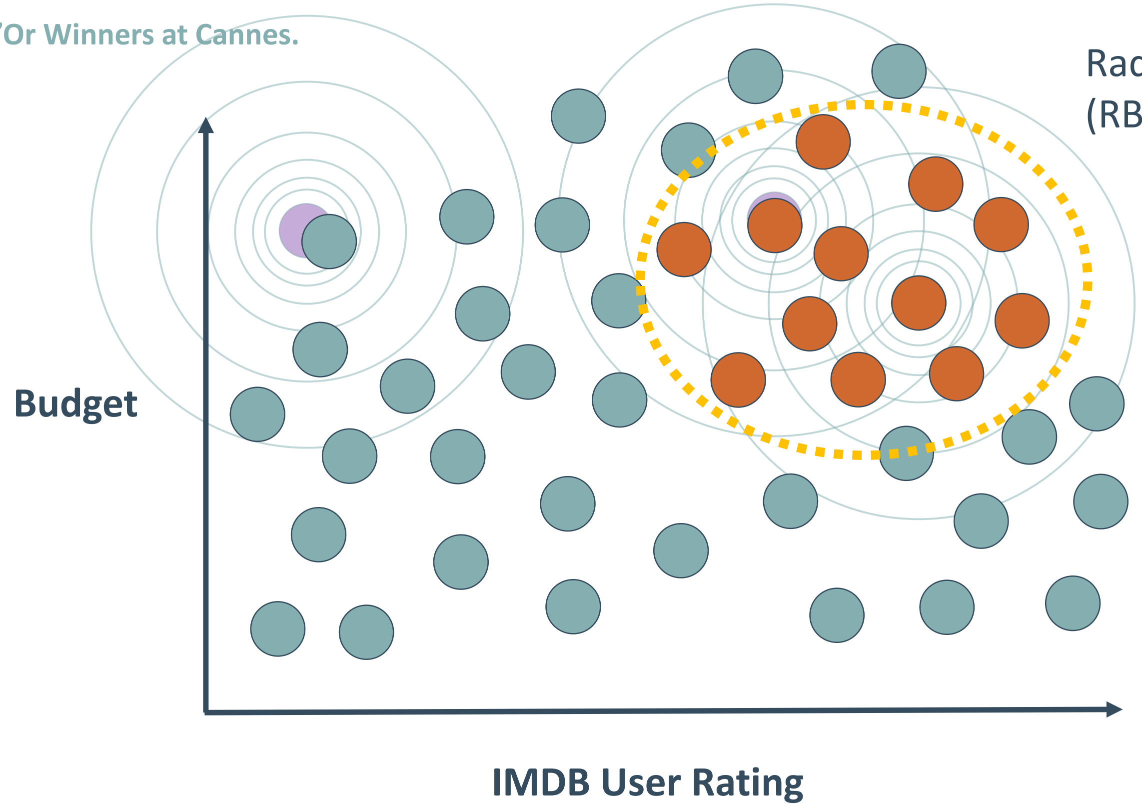

Radial Basis Function (RBF) Kernel.

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.

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

SVMs with Kernels: The Syntax

Import the class containing the classification method.

```
from sklearn.svm import SVC
```

Create an instance of the class.

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

Set kernel and associated coefficient (gamma).

SVMs with Kernels: The Syntax

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from sklearn.svm import SVC
```

Create an instance of the class.

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

"C" is penalty associated with the error term.

SVMs with Kernels: The Syntax

Import the class containing the classification method.

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from sklearn.svm import SVC
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Create an instance of the class.

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

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

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)
```

Multiple non-linear kernels can be used.

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 Nystroem
```

Create an instance of the class.

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

Kernel and gamma are identical to SVC.

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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```
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```

Create an instance of the class.

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

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.

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

Create an instance of the class.

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

RBF is only kernel that can be used.

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.

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

Create an instance of the class.

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

Parameter names are identical to previous.

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.

When to Use Logistic Regression vs SVC

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

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