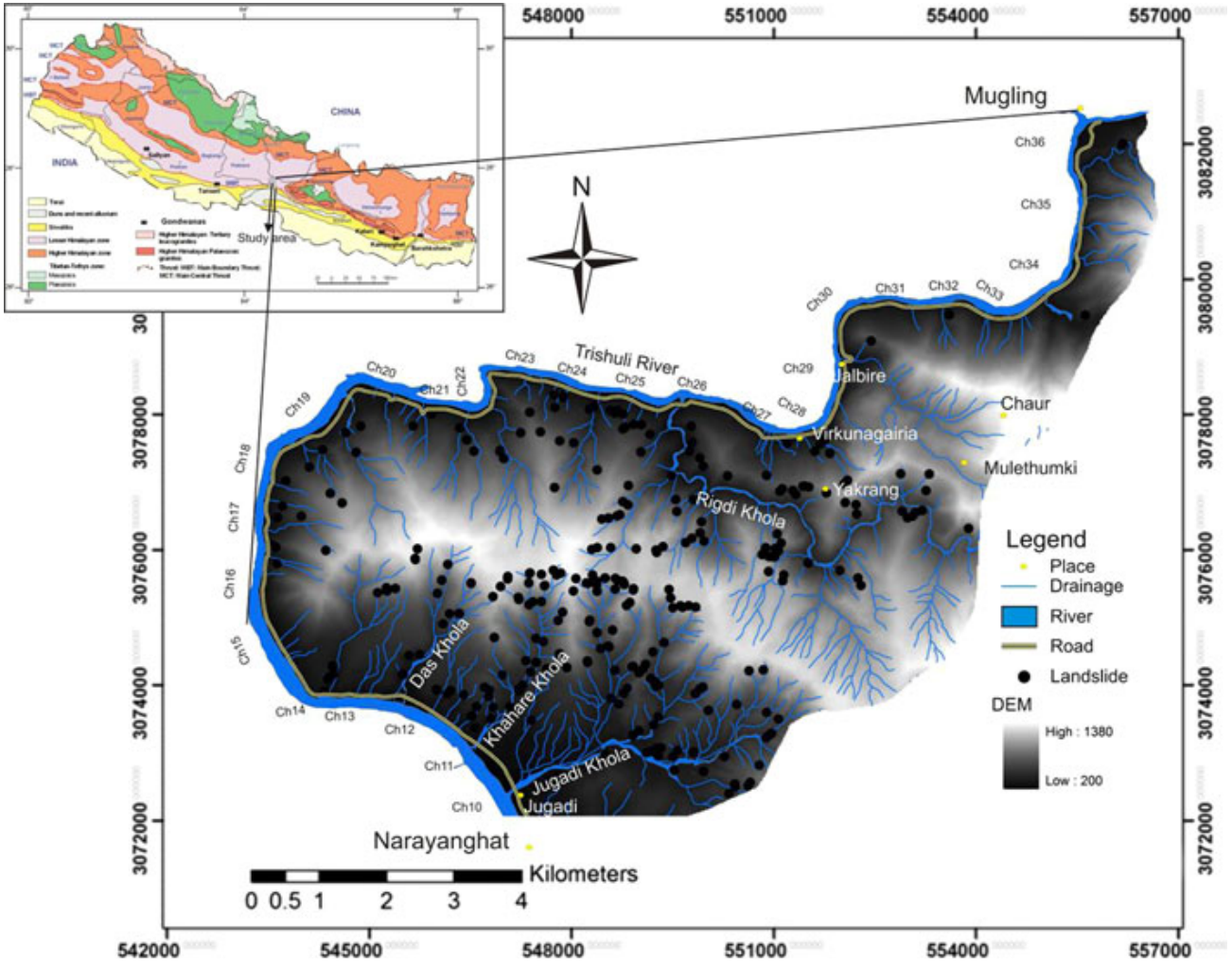
Estrada de 36km que liga Mugling–Narayanghat (Distrito Chitwan, Nepal central)



A susceptibilidade ao deslizamento é a probabilidade de uma ocorrência de deslizamento de terra em uma dada área. É o grau em que um terreno pode ser afetado por movimentos de declive, ou seja, uma estimativa de onde deslizamentos podem ocorrer.

Devkota, K. C., Regmi, A. D., Pourghasemi, H. R., Yoshida, K., Pradhan, B., Ryu, I. C., ... & Althuwaynee, O. F. (2013). Landslide susceptibility mapping using certainty factor, index of entropy and logistic regression models in GIS and their comparison at Mugling–Narayanghat road section in Nepal Himalaya. *Natural hazards*, *65*(1), 135-165.

Fatores condicionantes (características):

- *gradiente de inclinação,*
- *aspecto da inclinação,*
- *curvatura do plano,*
- *altitude,*
- *índice de potência da corrente (SPI),*
- *índice de umidade topográfica (TWI),*
- *índice de transporte de sedimentos do fluxo (ITS),*
- *geologia,*
- *uso do solo,*
- *distância das falhas,*
- *distância dos rios e*
- *distância das estradas.*

Variável dependente (y) é uma variável binária representando a presença ou ausência de deslizamentos.

$$\frac{p}{(1-p)}$$

p = probabilidade de ocorrer um deslizamento [0, 1]

$$logit(p) = ln \frac{p}{1-p}$$

[- ∞, + ∞]

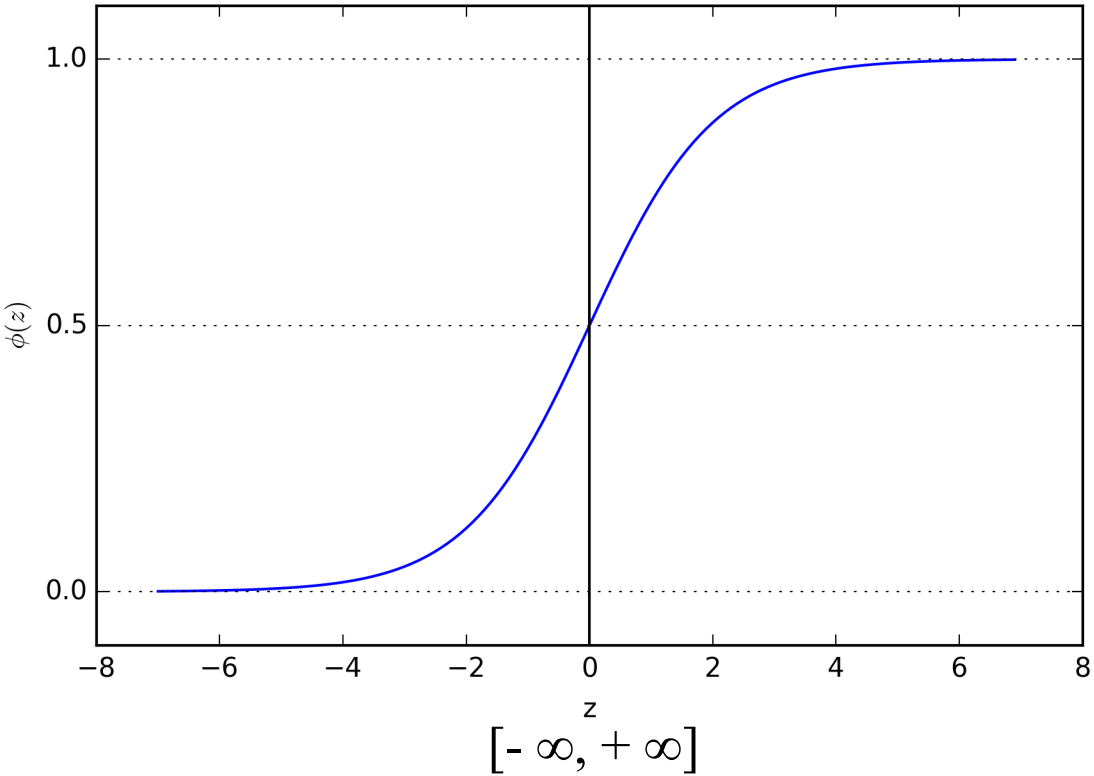
$$logit(p(y=1|\mathbf{x})) = w_0 x_0 + w_1 x_1 + \cdots + x_m w_m = \sum_{i=0}^{m} w_i x_i = \mathbf{w}^T \mathbf{x} = z$$

$$\frac{p}{1-p} = e^z \quad => \quad p = \phi(z) = \frac{1}{1+e^{-z}}$$

: função *logistic*

$$\phi(z) = \frac{1}{1 + e^{-z}} \quad : \textit{sigmoid}$$

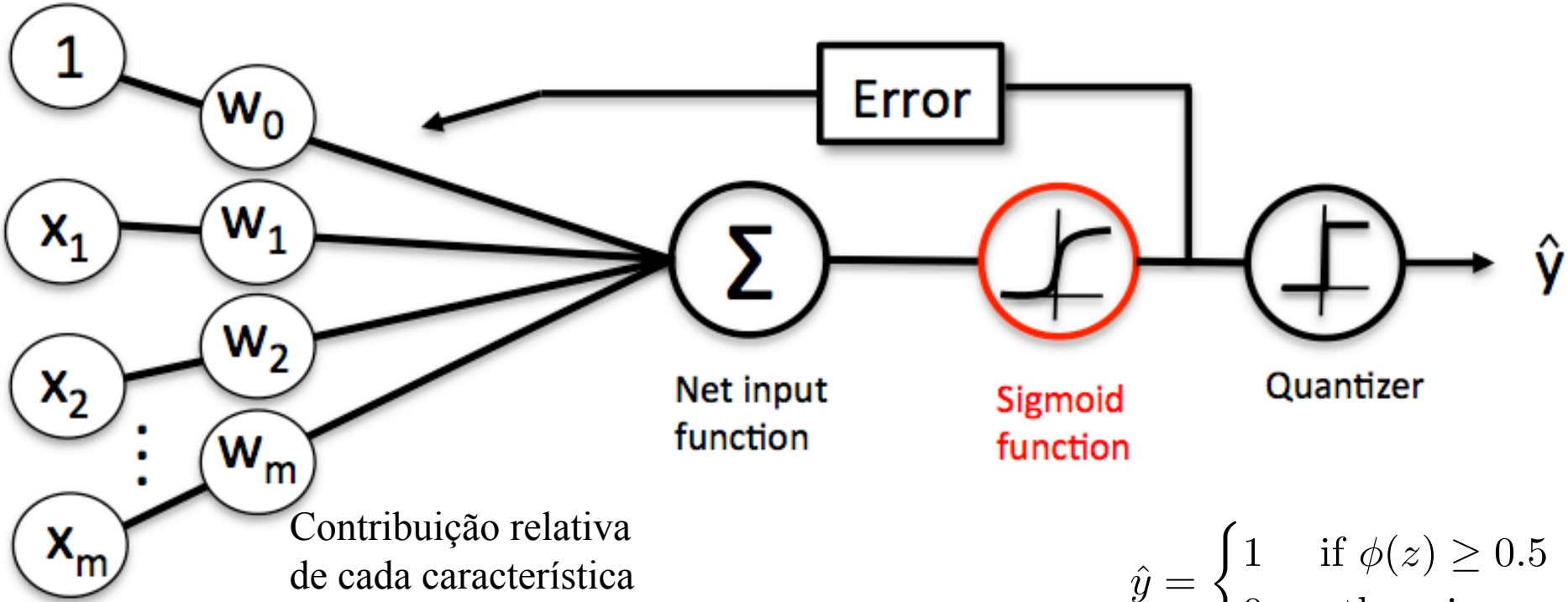
[0, 1]



[- ∞, + ∞]

Regressão logística

$$z = w_0 x_0 + w_1 x_1 + \cdots + x_m w_m = \sum_{i=0}^{m} w_i x_i = \mathbf{w}^T \mathbf{x}$$



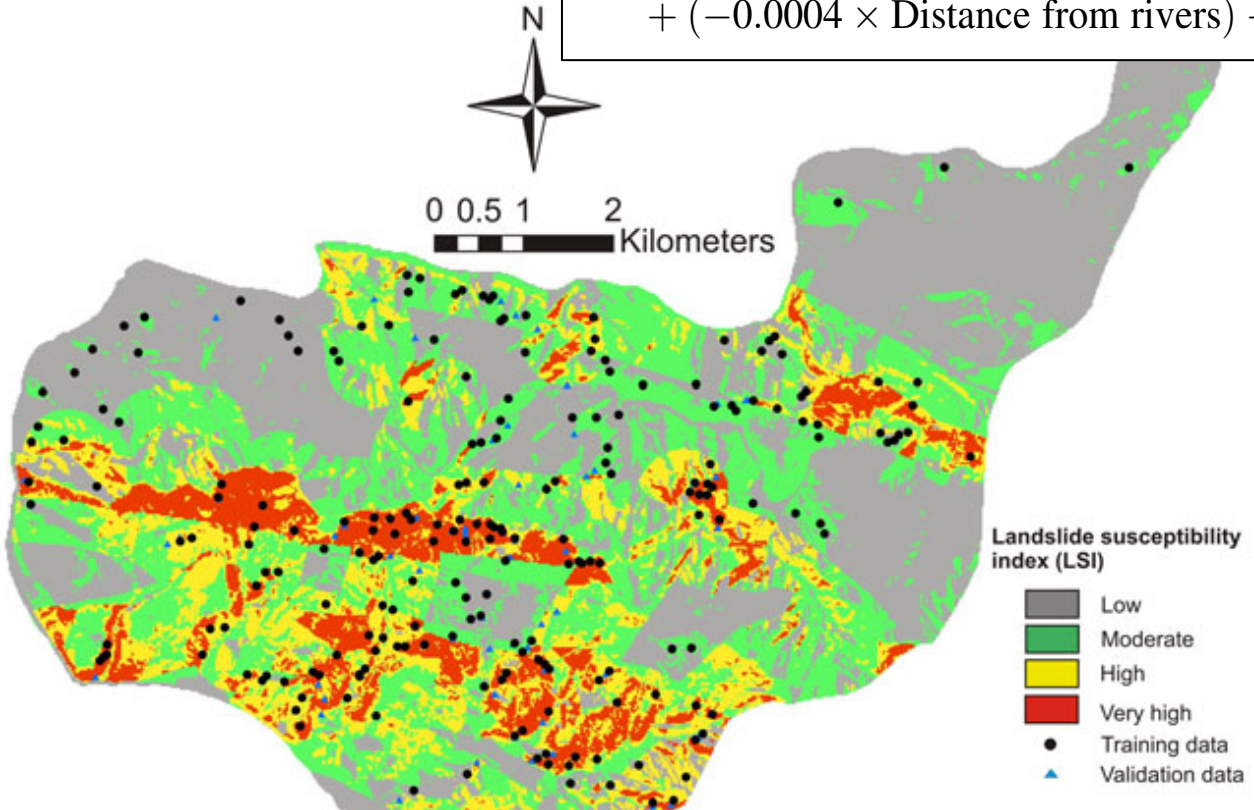
Variáveis independentes

Contribuição relativa de cada característica à função logística

$$\hat{y} = \begin{cases} 1 & \text{if } \phi(z) \geq 0.5 \\ 0 & \text{otherwise .} \end{cases}$$

Resultados

$$z = (0.0214 \times \text{Slope}) + \text{Aspect} + (0.08 \times \text{Altitude}) + (0.0221 \times \text{Plan curvature}) + (0.038 \times \text{SPI}) + (-0.2831 \times \text{TWI}) + (-0.002 \times \text{STI}) + \text{Lithology} + \text{Land use} + (-0.000041 \times \text{Distance from faults}) + (-0.00038 \times \text{Distance from roads}) + (-0.0004 \times \text{Distance from rivers}) - 18.991$$



Aprendizado dos pesos

Objetivo: maximizar a *Likelihood* (verossimilhança)

$$L(\mathbf{w}) = P(\mathbf{y}|\mathbf{x};\mathbf{w}) = \prod_{i=1}^{n} P\left(y^{(i)}|x^{(i)};\mathbf{w}\right) = \prod_{i=1}^{n} \left(\phi\left(z^{(i)}\right)\right)^{y^{(i)}} \left(1-\phi\left(z^{(i)}\right)\right)^{1-y^{(i)}}$$

Assume-se que as amostras individuais são independentes entre si

Mais fácil: maximizar a *Log-Likelihood* (log da verossimilhança)

$$l(\mathbf{w}) = \log L(\mathbf{w}) = \sum_{i=1}^{n} \left[y^{(i)} \log\left(\phi\left(z^{(i)}\right)\right) + \left(1-y^{(i)}\right) \log\left(1-\phi\left(z^{(i)}\right)\right) \right]$$

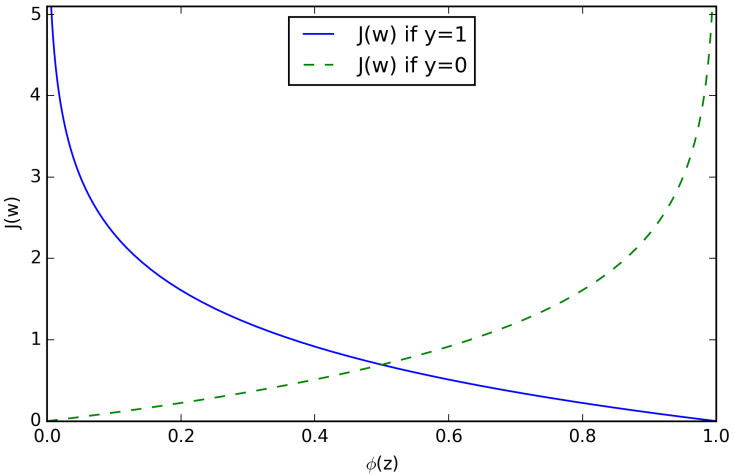
Aprendizado dos pesos

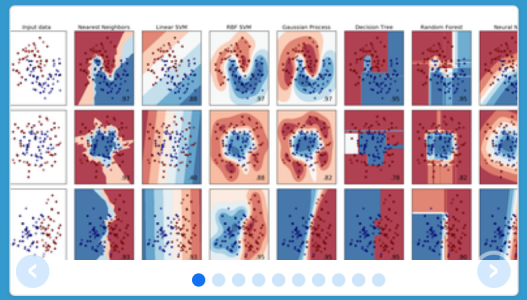
...ou minimizar a função de custo equivalente.

$$J(\mathbf{w}) = \sum_{i=1}^{n} \left[-y^{(i)} \log\left(\phi\left(z^{(i)}\right)\right) - \left(1 - y^{(i)}\right) \log\left(1 - \phi\left(z^{(i)}\right)\right) \right]$$

$$J\left(\phi(z), y; \mathbf{w}\right) = -y \log\left(\phi(z)\right) - (1 - y) \log\left(1 - \phi(z)\right).$$

$$J\left(\phi(z), y; \mathbf{w}\right) = \begin{cases} -\log\left(\phi(z)\right) \text{ if } y = 1 \\ -\log\left(1 - \phi(z)\right) \text{ if } y = 0 \end{cases}$$





scikit-learn

Machine Learning in Python

- Simple and efficient tools for data mining and data analysis
- Accessible to everybody, and reusable in various contexts
- Built on NumPy, SciPy, and matplotlib
- Open source, commercially usable - BSD license

Classification

Identifying to which category an object belongs to.

Applications: Spam detection, Image recognition.
Algorithms: SVM, nearest neighbors, random forest, ... — Examples

Regression

Predicting a continuous-valued attribute associated with an object.

Applications: Drug response, Stock prices.
Algorithms: SVR, ridge regression, Lasso, ... — Examples

Clustering

Automatic grouping of similar objects into sets.

Applications: Customer segmentation, Grouping experiment outcomes
Algorithms: k-Means, spectral clustering, mean-shift, ... — Examples

Dimensionality reduction

Reducing the number of random variables to consider.

Applications: Visualization, Increased efficiency
Algorithms: PCA, feature selection, non-negative matrix factorization. — Examples

Model selection

Comparing, validating and choosing parameters and models.

Goal: Improved accuracy via parameter tuning
Modules: grid search, cross validation, metrics. — Examples

Preprocessing

Feature extraction and normalization.

Application: Transforming input data such as text for use with machine learning algorithms.
Modules: preprocessing, feature extraction. — Examples

Exemplo: base Íris

```
from sklearn import datasets
import numpy as np

iris = datasets.load_iris()
X = iris.data[:, [2, 3]]
y = iris.target

print('Class labels:', np.unique(y))
```

Leitura da base

```
from sklearn.preprocessing import StandardScaler

sc = StandardScaler()
sc.fit(X_train)
X_train_std = sc.transform(X_train)
X_test_std = sc.transform(X_test)
```

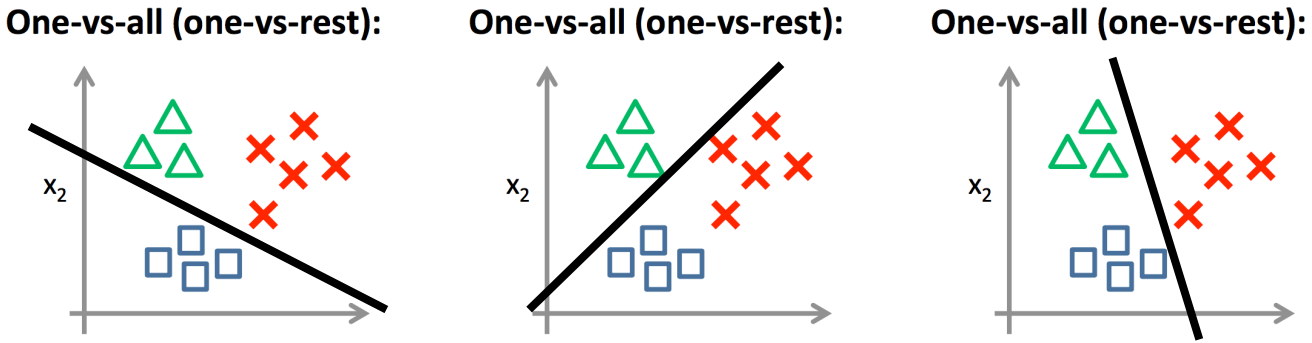
???

Treinamento

```
from sklearn.linear_model import LogisticRegression

lr = LogisticRegression(C=1000.0, random_state=0)
lr.fit(X_train_std, y_train)

plot_decision_regions(X_combined_std, y_combined,
                      classifier=lr, test_idx=range(105, 150))
```



Teste

```
from sklearn.linear_model import LogisticRegression

lr = LogisticRegression(C=1000.0, random_state=0)
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plot_decision_regions(X_combined_std, y_combined,
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```
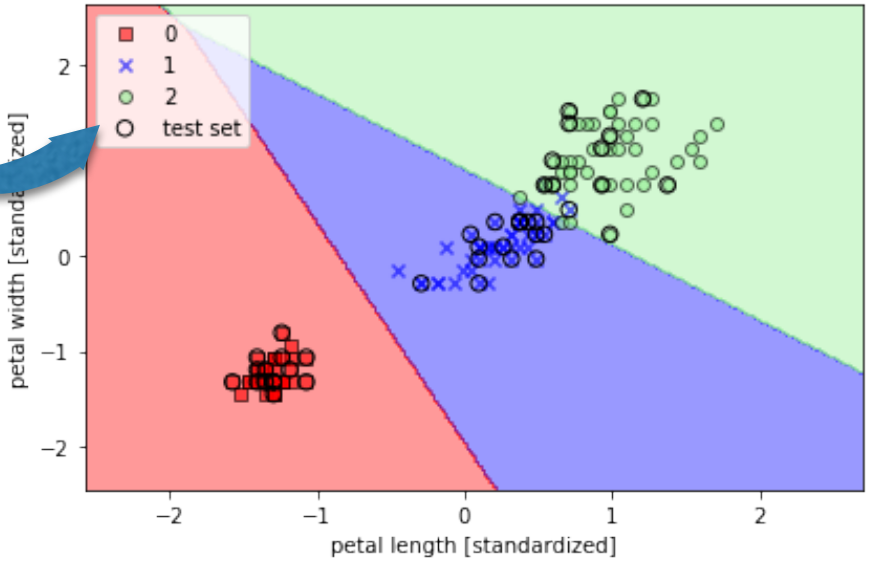



Execução do modelo

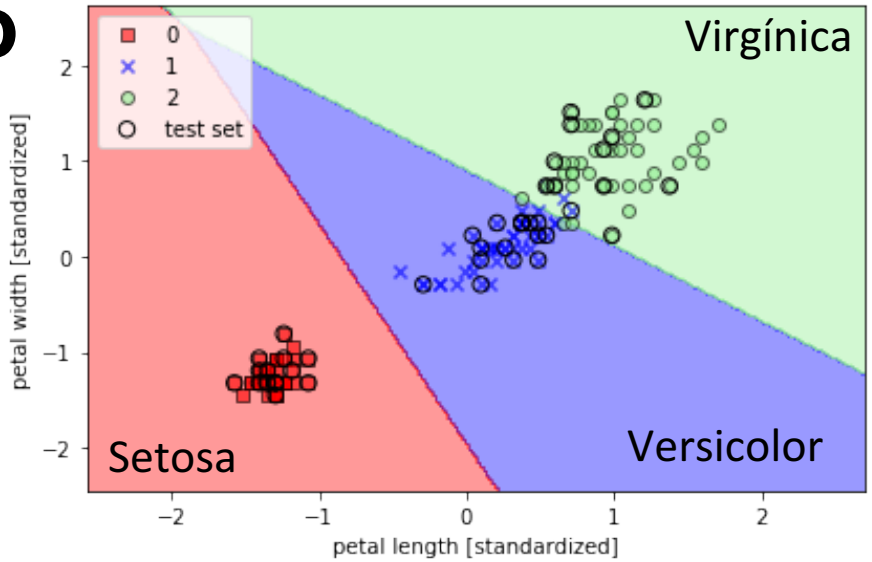
Amostras

lr.predict_proba(X_test_std[17,:])

```
array([[ 0.000, 0.995, 0.005]])
```

lr.predict_proba(X_test_std[37,:])

```
array([[ 0.000, 0.383, 0.617]])
```



Problemas com o treinamento de modelos

Overfitting (super-especialização) = Modelo com alta variância

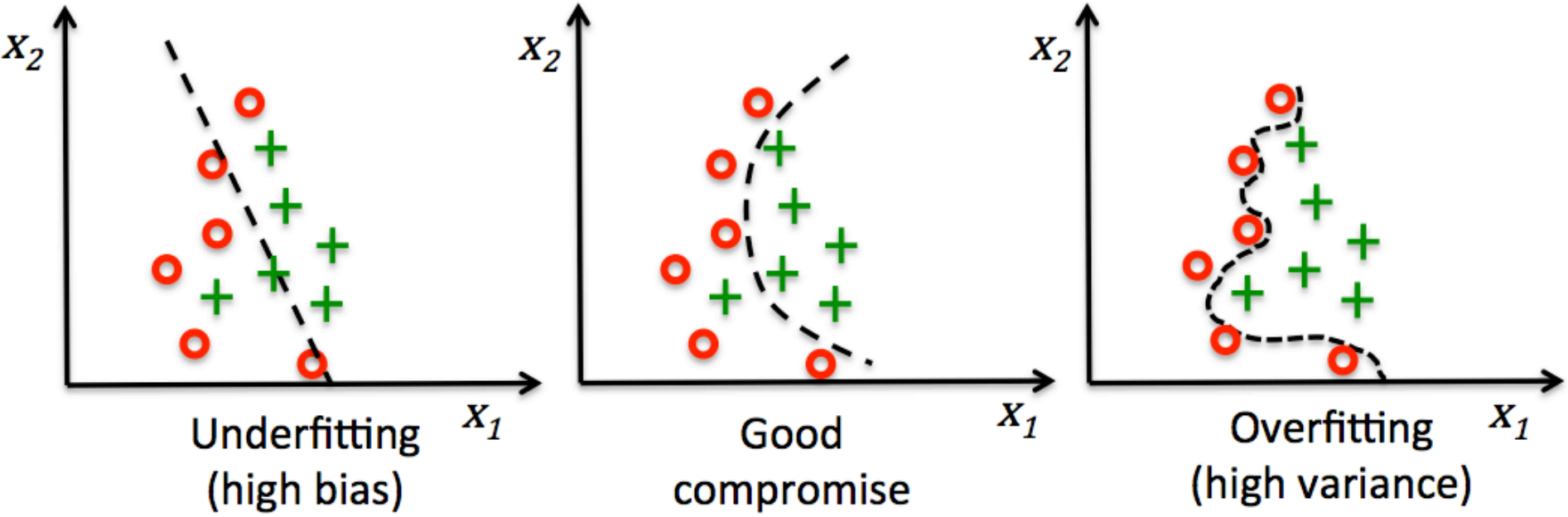
- Pode ser causado por uma quantidade **muito grande de parâmetros** que faz o **modelo complexo demais** em relação aos dados

Mede o quanto um modelo é sensível à aleatoriedade dos dados de treinamento

Underfitting (sub-especialização) = Modelo com alto viés (bias)

- Modelo **não é complexo o suficiente** para capturar o padrão nos dados de treinamento

Mede o erro sistemático do modelo, que não é afetado pela aleatoriedade dos dados de treino


x_2
x_1
Underfitting
(high bias)
x_2
x_1
Good
compromise
x_2
x_1
Overfitting
(high variance)

Método para encontrar um bom **tradeoff *bias-variance***

Regularização

Rationale: introduzir informação adicional para penalizar valores muito altos de pesos

Regularização *L2*

Aumento => maior poder de regularização

$$J(\mathbf{w}) = -\sum_{i=1}^{n}\left[y^{(i)}\log\left(\phi(z^{(i)})\right) - \left(1-y^{(i)}\right)\log\left(1-\phi(z^{(i)})\right)\right] + \frac{\lambda}{2}\|\mathbf{w}\|^2$$

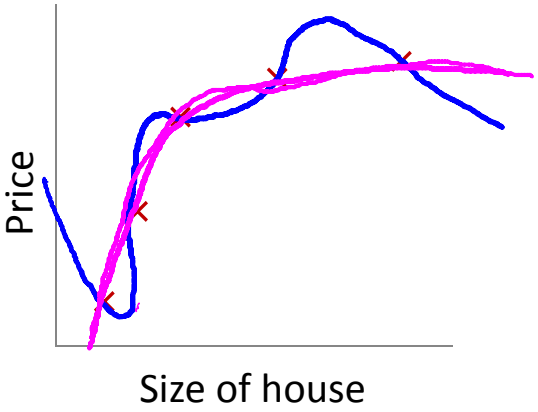
$$\frac{\lambda}{2}\|\mathbf{w}\|^2 = \frac{\lambda}{2}\sum_{j=1}^{m} w_j^2$$

$$\Delta w_j = -\eta\frac{\partial J}{\partial w_j} = \eta\sum_{i=1}^{n}\left(y^{(i)} - \phi(z^{(i)})\right)x_j^{(i)} - \eta\lambda w_j$$

for $j \in \{1, 2, ..., m\}$ (i.e., $j \neq 0$) pois o peso w_0 não passa por regularização.

Regularização *L2* ...: intuição

$$J(\mathbf{w}) = -\sum_{i=1}^{n}\left[y^{(i)}\log\left(\phi(z^{(i)})\right) - \left(1-y^{(i)}\right)\log\left(1-\phi(z^{(i)})\right)\right] + \frac{\lambda}{2}\|\mathbf{w}\|^2$$



$$w_0 + w_1 x_1 + \cdots + x_m w_m$$

Q: What if λ is set to an extremely large value (perhaps for too large for our problem, say $\lambda = 10^{10}$)?

a. Algorithm works fine; setting λ to be very large can't hurt it
b. Algortihm fails to eliminate overfitting.
c. Algorithm results in underfitting. (Fails to fit even training data well).
d. Gradient descent will fail to converge.

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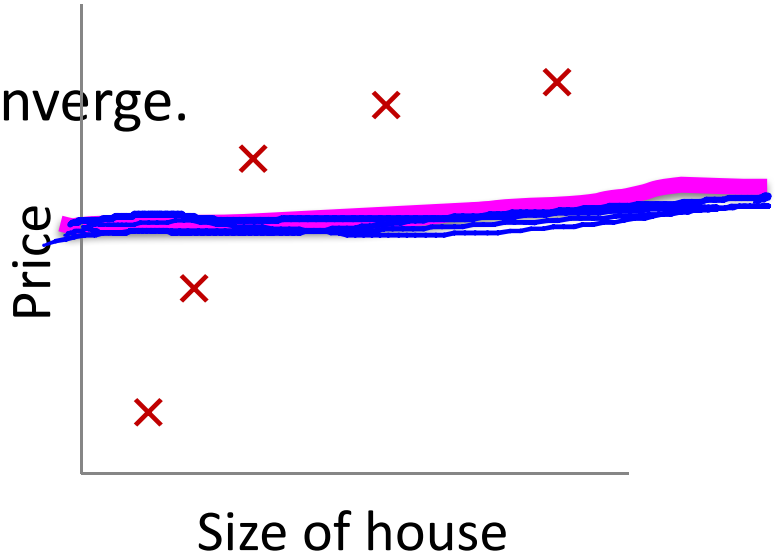
$$w_0 + w_1 x_1 + \cdots + x_m w_m$$



Regularização *L2*

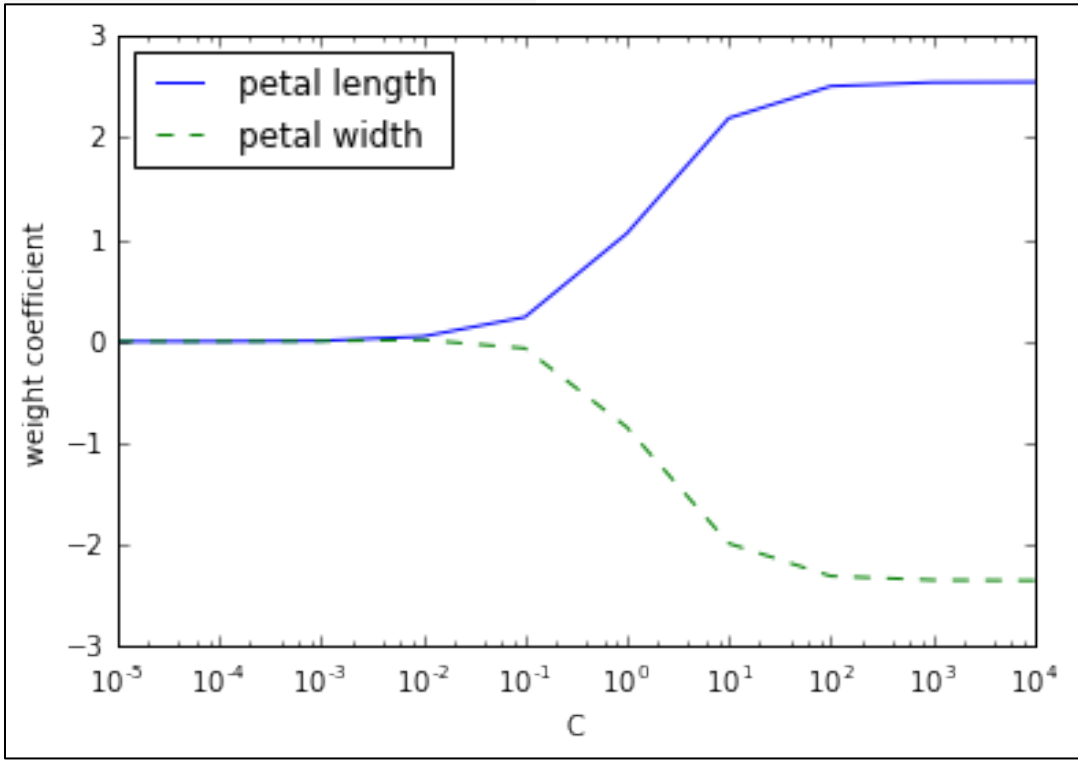
$$J(\mathbf{w}) = -\sum_{i=1}^{n}\left[y^{(i)}\log\left(\phi(z^{(i)})\right) - \left(1-y^{(i)}\right)\log\left(1-\phi(z^{(i)})\right)\right] + \frac{\lambda}{2}\|\mathbf{w}\|^2$$

Se $C = \frac{1}{\lambda}$

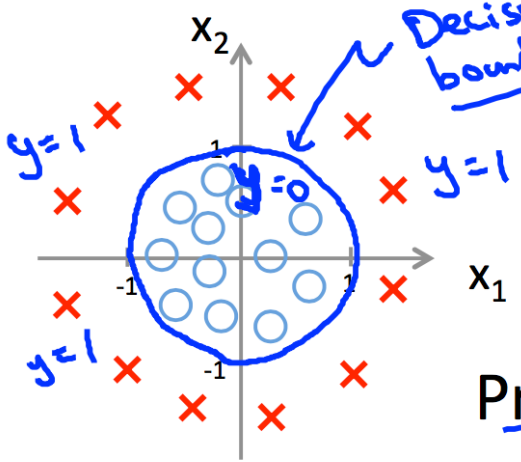
$$J(\mathbf{w}) = C\left[\sum_{i=1}^{n}\left(-y^{(i)}\log\left(\phi(z^{(i)})\right) - \left(1-y^{(i)}\right)\right)\log\left(1-\phi(z^{(i)})\right)\right] + \frac{1}{2}\|\mathbf{w}\|^2$$

```
weights, params = [], []
for c in np.arange(-5, 5):
    lr = LogisticRegression(C=10**c, random_state=0)
    lr.fit(X_train_std, y_train)
    weights.append(lr.coef_[1])
    params.append(10**c)

weights = np.array(weights)
```



Limites de decisão não lineares

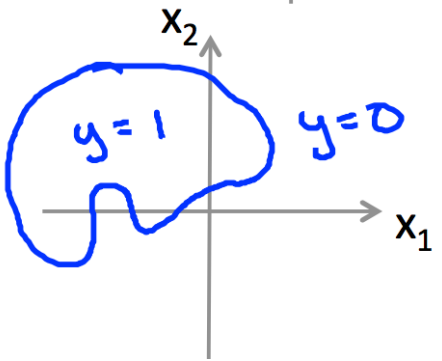


$$h_\theta(x) = g(w_0 + w_1 x_1 + w_2 x_2 + w_3 x_1^2 + w_4 x_2^2)$$

$\theta = \begin{bmatrix} -1 \\ 0 \\ 0 \\ 1 \\ 1 \end{bmatrix}$

Predict "$y = 1$" if $-1 + x_1^2 + x_2^2 \geq 0$

$x_1^2 + x_2^2 \geq 1$



$$h_\theta(x) = g(w_0 + w_1 x_1 + w_2 x_2 + w_3 x_1^2 + w_4 x_1^2 x_2 + w_5 x_1^2 x_2^2 + w_6 x_1^3 x_2 + \ldots)$$

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