

# Combinação de Modelos (Ensembles)

Prof. André Gustavo Hochuli

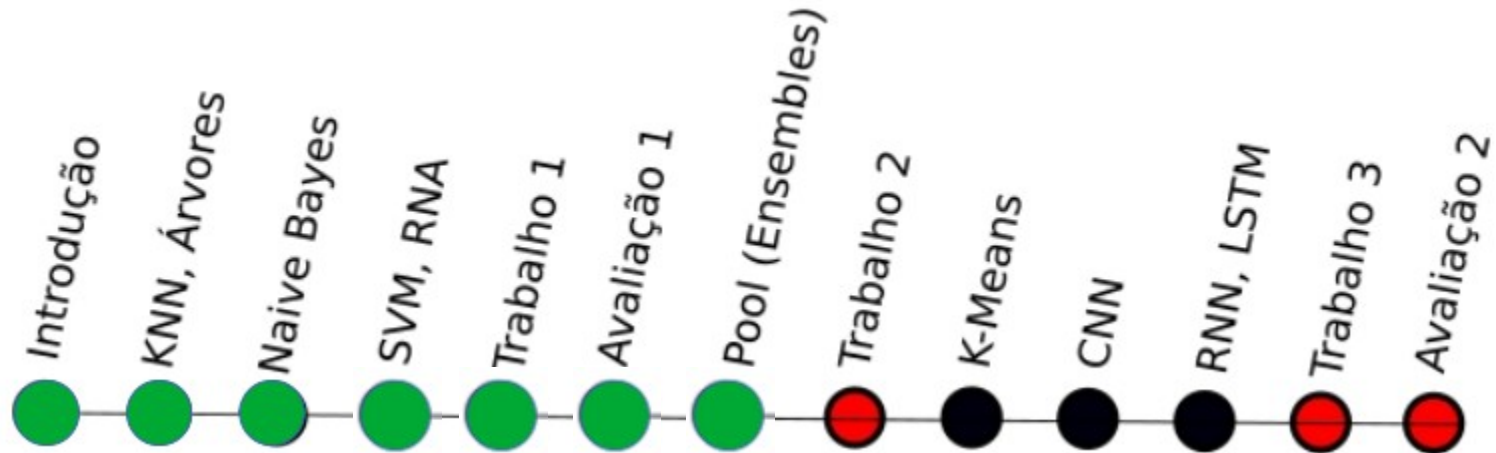
[gustavo.hochuli@pucpr.br](mailto:gustavo.hochuli@pucpr.br)

[aghochuli@ppgia.pucpr.br](mailto:aghochuli@ppgia.pucpr.br)

[github.com/andrehochuli/teaching](https://github.com/andrehochuli/teaching)

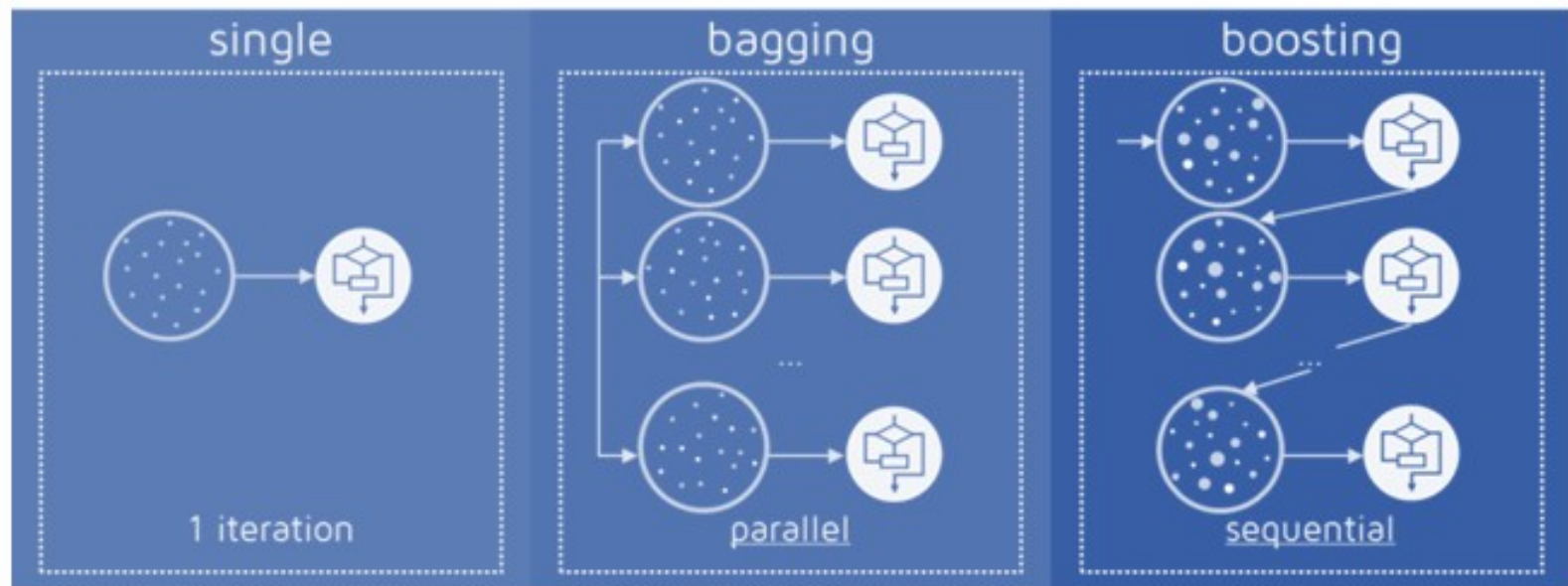
# Plano de Aula

- Discussões Iniciais
- Combinação
  - Bagging
  - Random Subspaces
  - Boosting
  - Stacking
- Exercícios



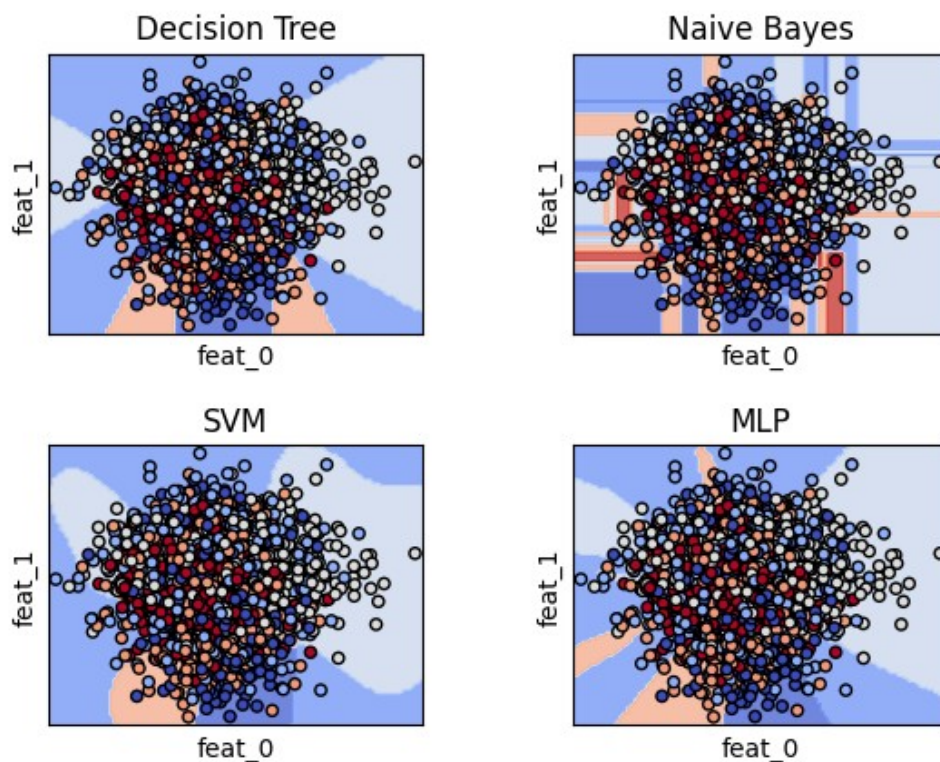
# Discussões Iniciais

- Classificador Único
- Conjunto de Classificadores



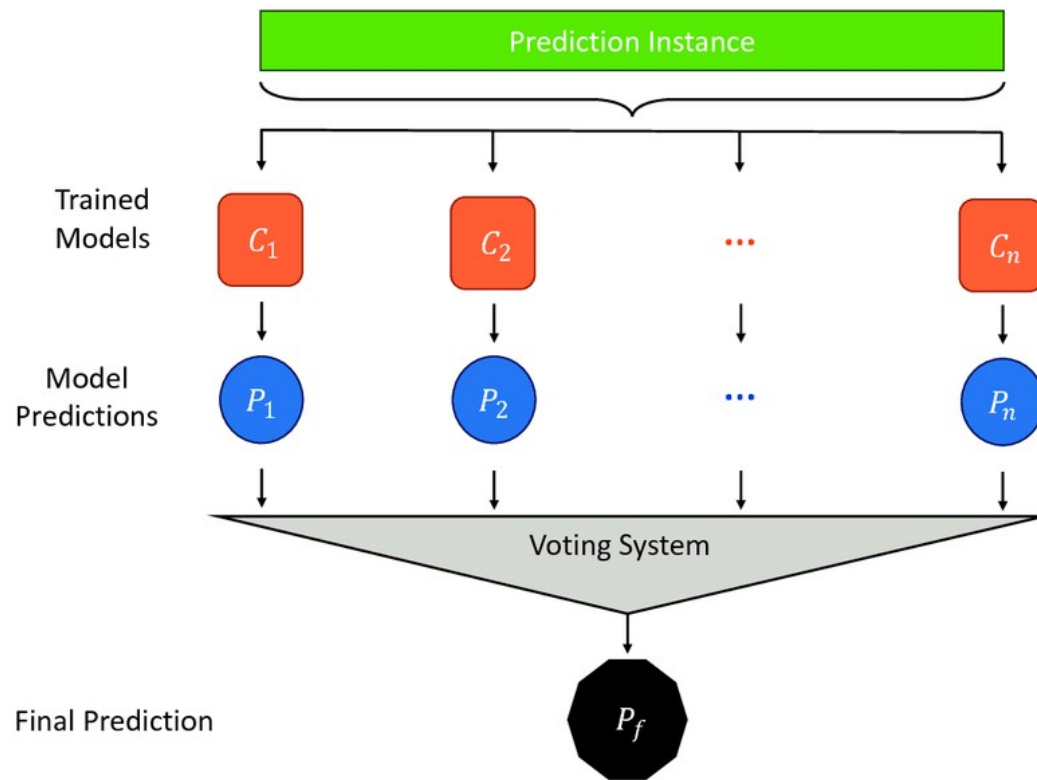
# Combinação de classificadores

- Em problemas complexos, um único classificador pode não generalizar adequadamente o problema
- E se combinarmos classificadores?



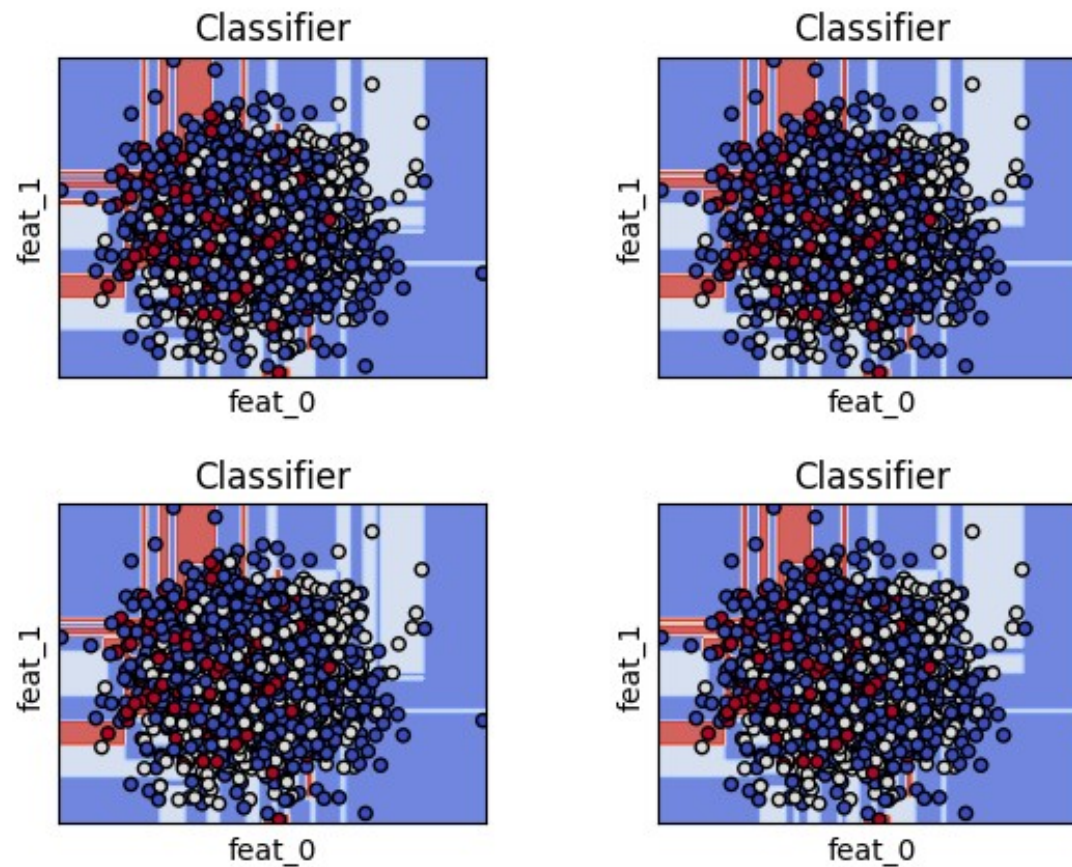
# Combinação de classificadores

- De maneira geral, a técnica consiste em treinar classificadores e então combinar a saída destes



# Combinação de classificadores

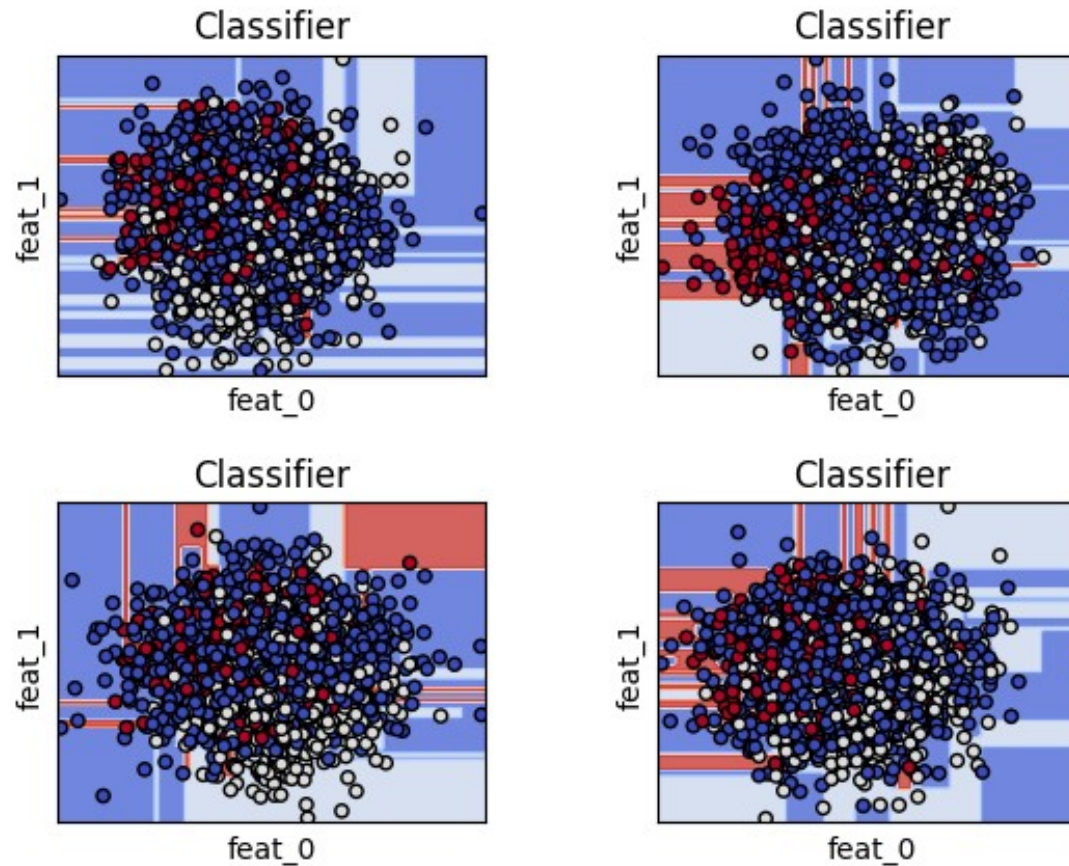
Porém, apenas treinar N classificadores, pode não gerar generalizações distintas





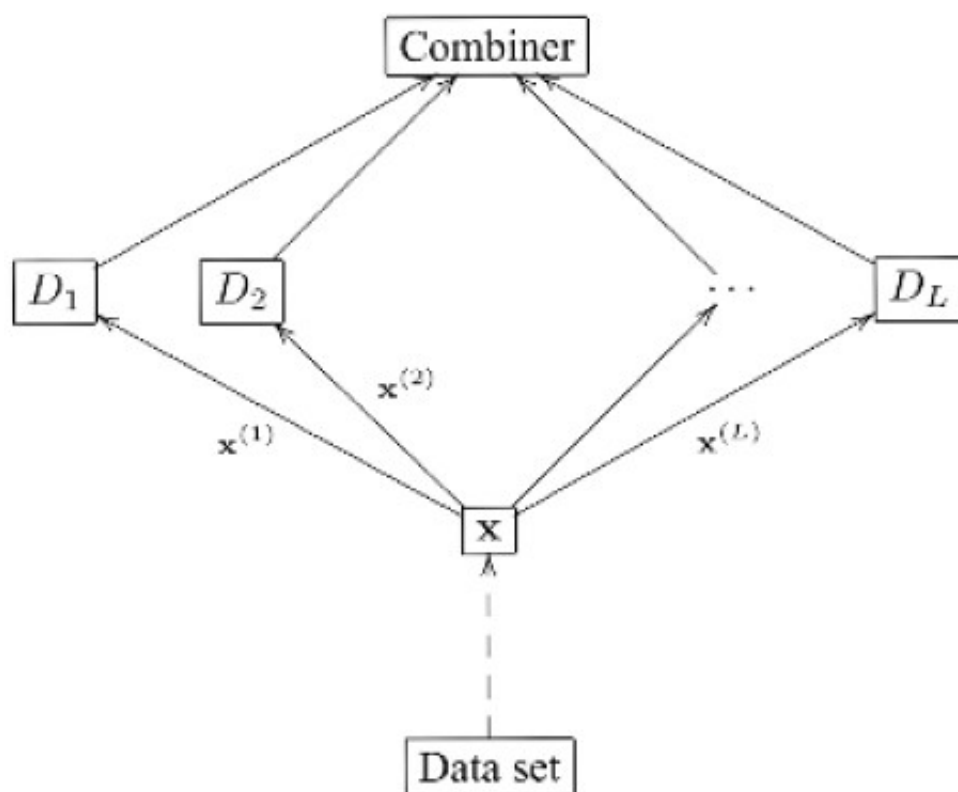
# Combinação de classificadores

- Pergunta: Como gerar generalizações diferentes ?



# Combinação de classificadores

- Pergunta: Como gerar generalizações diferentes ?



**A.** *Combination level:*  
Design different  
combiners.

**B.** *Classifier level:*  
Use different  
base classifiers.

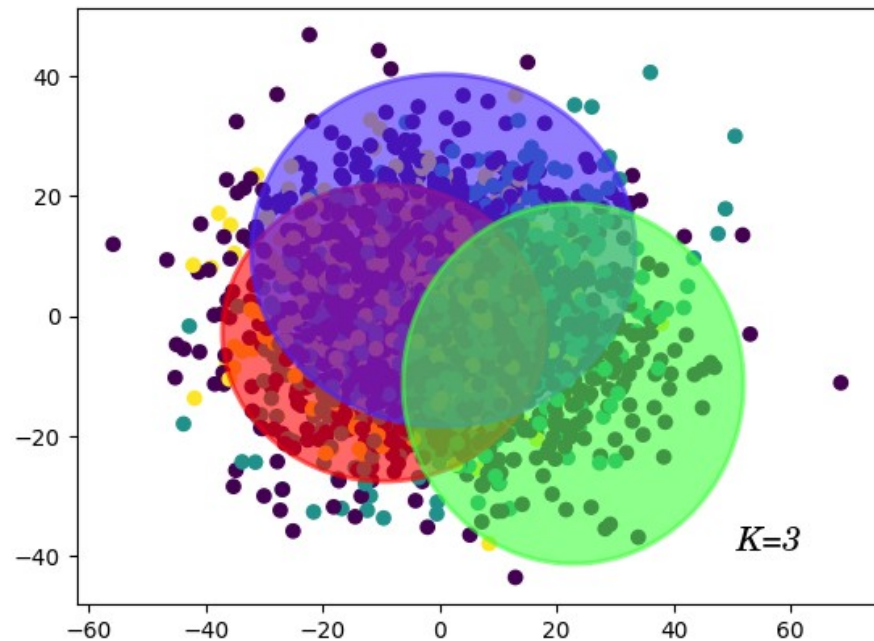
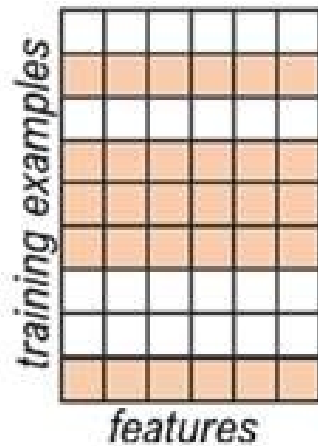
**C.** *Feature level:*  
Use different  
feature subsets.

**D.** *Data level:*  
Use different  
data subsets.



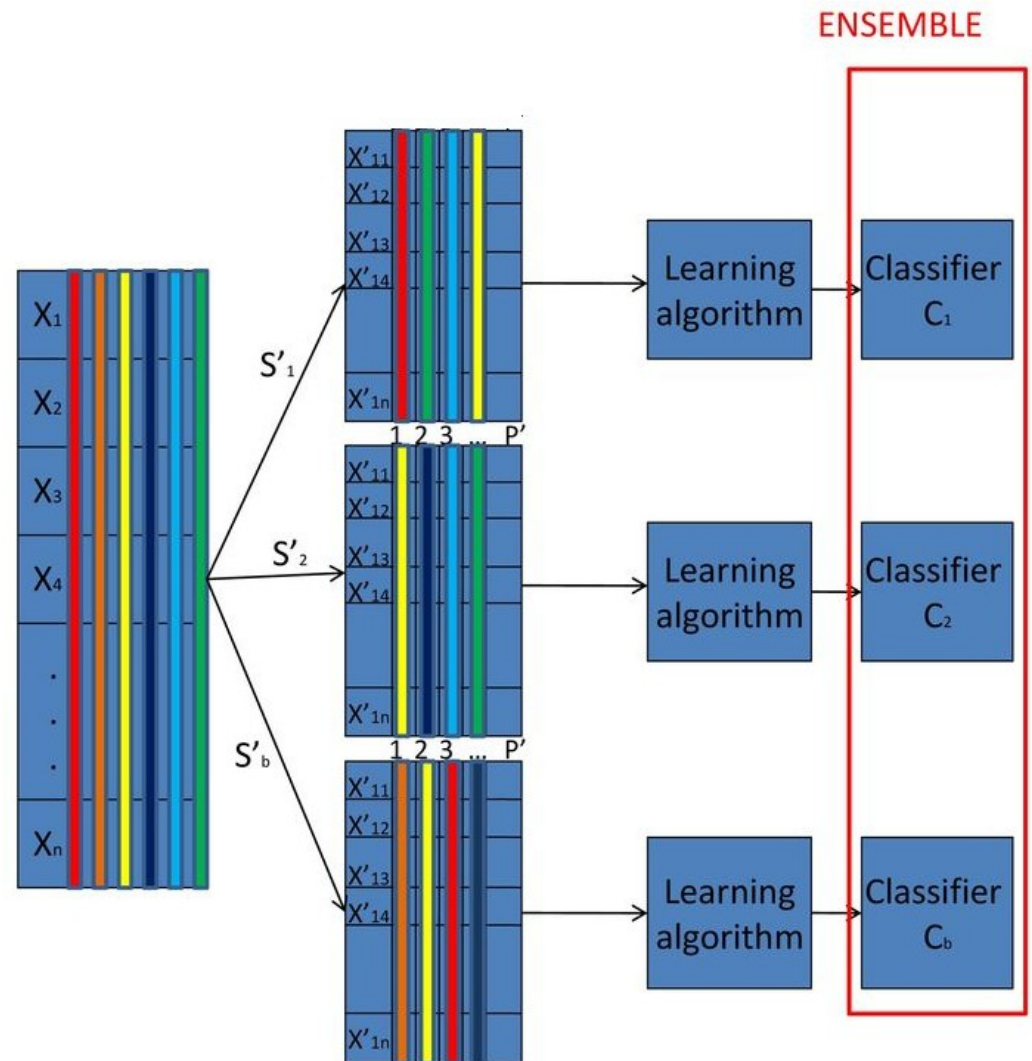
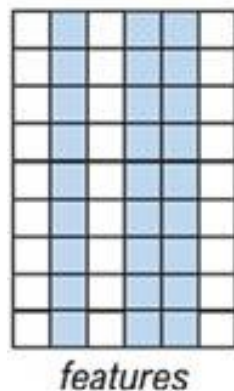
# Bagging

- Nível de Dados: (Bootstrap Aggregating)
  - K subsets em nível de instâncias
  - K classificadores
- Diversidade é gerada a partir das distintas instâncias



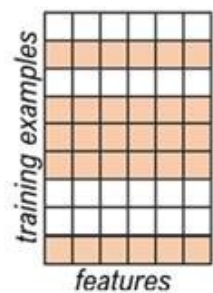
# Random SubSpaces

- Nível de Atributos:
  - K subsets em nível de atributos
  - K classificadores
- Diversidade: Distintos atributos



# Random Patches

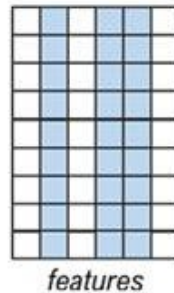
- Tudo Junto!
- Sklearn: BaggingClassifier()



## bagging

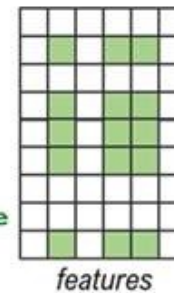
(sample instances)

`max_samples=0.75,`  
`bootstrap=True,`  
`max_features=1.0,`  
`bootstrap_features=False`



random subspaces  
(sample features)

`max_samples=1.0,`  
`bootstrap=False,`  
`max_features=0.5,`  
`bootstrap_features=True`



random patches  
(sample both)

`max_samples=0.75,`  
`bootstrap=True,`  
`max_features=0.5,`  
`bootstrap_features=True`

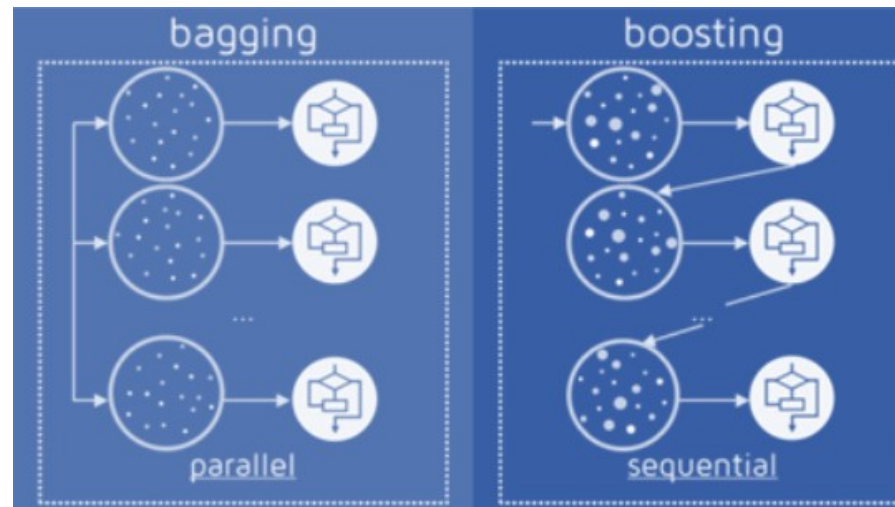
# Let's Code!

- No tutorial abaixo, exploraremos os conceitos abordados até o momento:

LINK: [Tópico 02 - Aprendizado-Supervisionado - Ensembles.ipynb](#)

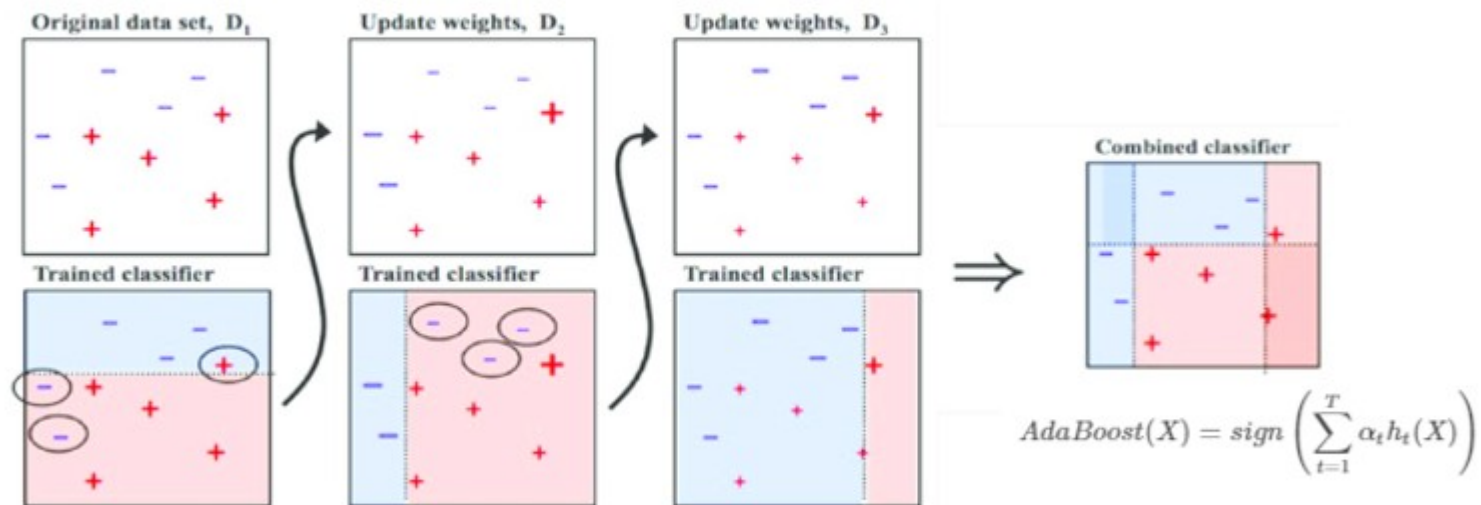
# Boosting

- N classificadores 'fracos' organizados sequencialmente
- O classificador N aprende sobre os erros do classificador N-1
- Cada classificador tem um peso no conjunto, determinado pelo seu erro



# Boosting

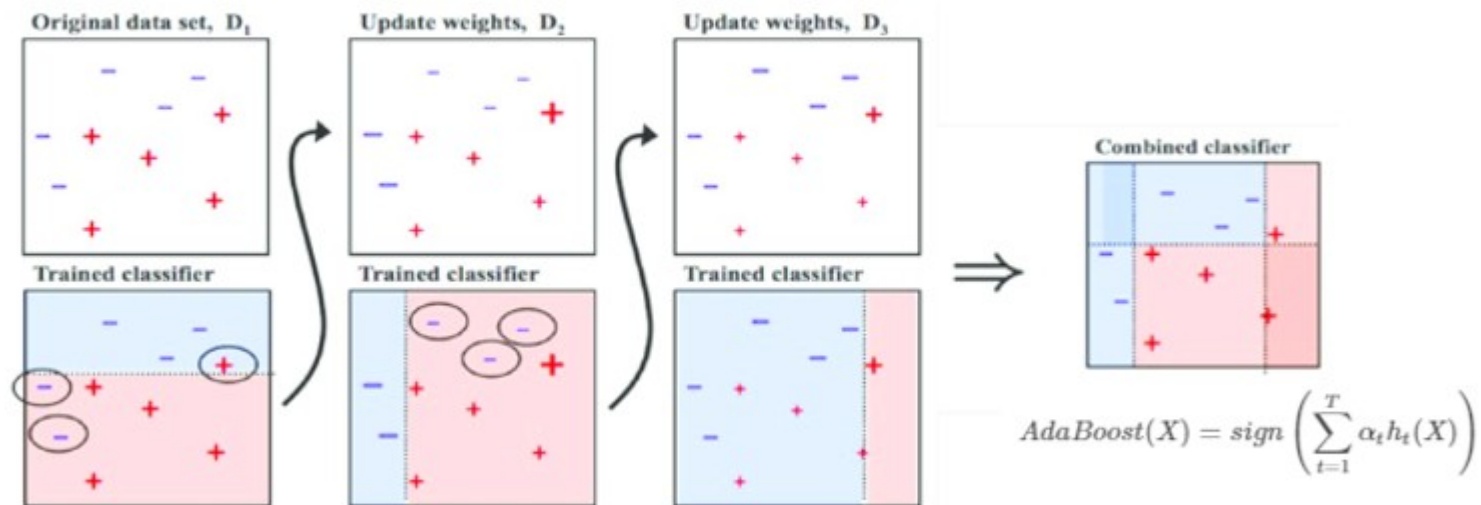
- Pseudo-algoritmo:
  - Treinar um classificador 'fraco' ponderando as instâncias
  - Determinar o erro
  - Ponderar as instâncias de acordo com o erro
  - Determinar o coeficiente do classificador (erro)
  - Adicionar ao ensemble





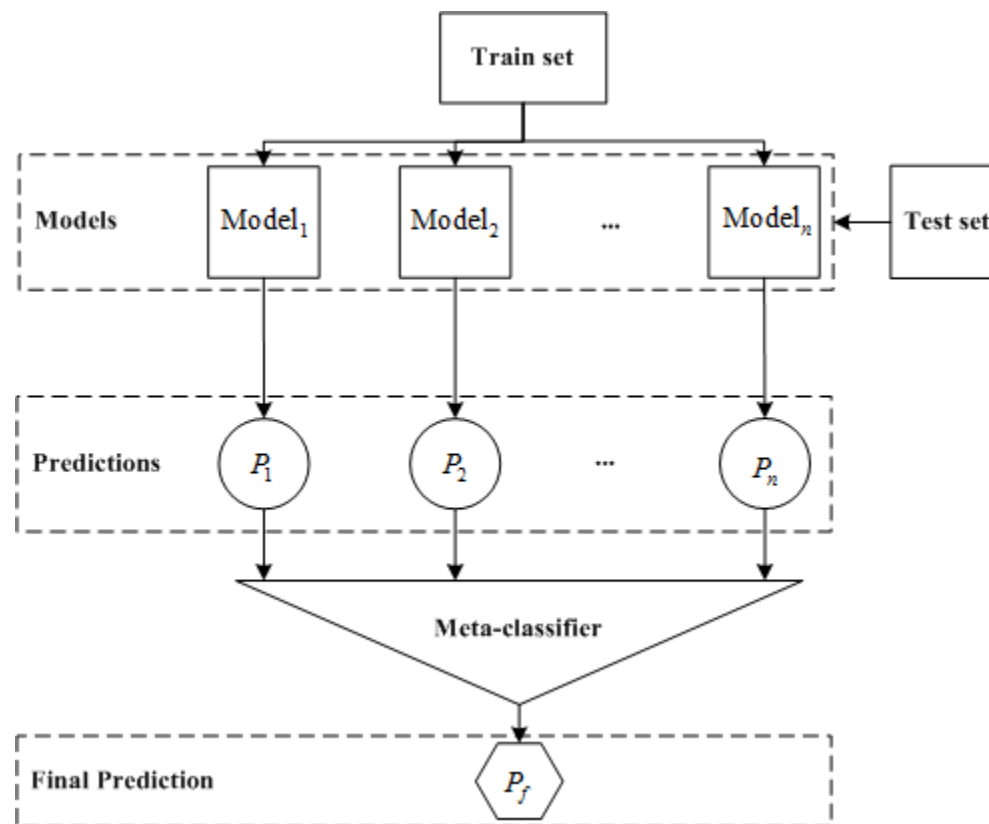
# Boosting

- Pseudo-algoritmo:
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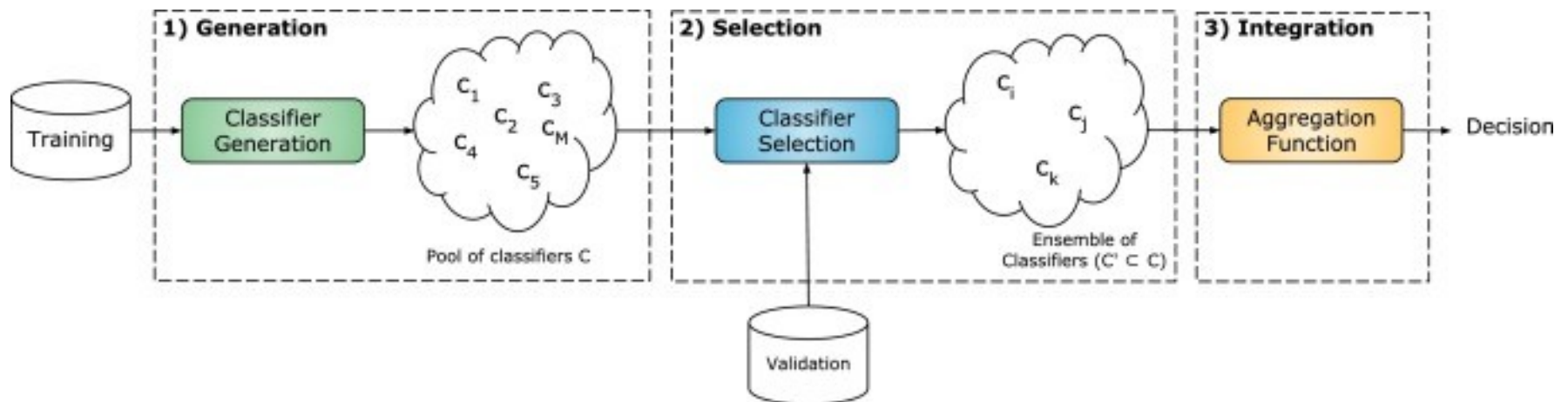
# Stacking

- Meta-classificador: Aprende com a saída dos classificadores



# Seleção Dinâmica

- Meta-Classifer determina a região de competência e seleciona o melhor classificador(es)



# Bagging vs Boosting

Bagging	Boosting
Both the ensemble methods get N learners from 1 learner. But..	
..follows parallel ensemble techniques, i.e. base learners are formed independently.	..follows Sequential ensemble technique, i.e. base learners are dependent on the previous weak base learner.
Random sampling with replacement.	Random sampling with replacement over weighted data.
Both gives out the final prediction by taking average of N learners. But..	
..equal weights is given to all model. (equally weighted average)	..more weight is given to the model with better performance. (weighted average)
Both are good at providing high model scalability. But..	
..it reduces variance and solves the problem of overfitting.	..it reduces the bias but is more prone to overfitting.  Overfitting can be avoided by tuning the parameters.

# Let's Code!

- Continuando no tutorial anterior, vamos analisar o AdaBoost

LINK: [Tópico 02 - Aprendizado-Supervisionado - Ensembles.ipynb](#)