

# Aprendizado de Máquina e Reconhecimento de Padrões 2021.2



## Hyperparameter Optimization (Fine-tuning)

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## Model Hyperparameters

Properties that are **external** to the model and whose value **cannot be estimated/learned from data**.

Examples:

- **Imputer's strategy**: 'median'
- **Number of neighbors for KNN**: 3

## Model Parameters

Properties that are **internal** to the model and whose value **can be estimated/learned from data**.

Examples:

- **Estimated value for missing values**: 20 (median)
- **Estimated coefficients of a linear regression**.

**Problem**  
Filling in missing values (imputer)

	Name	Age
0	John	19.0
1	Maria	22.0
2	Alice	18.0
3	Margot	20.0
4	Pedro	NaN
5	Giovanni	21.0

(training) data

**(hyperparameter)**  
**Imputer's strategy**: 'median'

**(parameter)**  
**estimated/learned value**: 20

# Hyperparameter Optimization (Fine-tuning)

- It is the problem of choosing a set of **optimal values** for **hyperparameters** for a **learning algorithm** and **data**.

hyperparameters  $\Psi$

A	B
1	9
3	14
4	12
8	18
12	20

$$\boldsymbol{\varphi}^* = \operatorname{argmax}_{\boldsymbol{\varphi}_i \in \Psi} f(\boldsymbol{\varphi})$$



$\Psi$ : all hyperparameter combinations/sets

$\boldsymbol{\varphi}_i$ : i-th hyperparameter combination/set from  $\Psi$

$f(\boldsymbol{\varphi})$ : training and validation of the ML algorithm with  $\boldsymbol{\varphi}$

$\boldsymbol{\varphi}^*$ : optimum hyperparameter combination

# Holdout Strategy

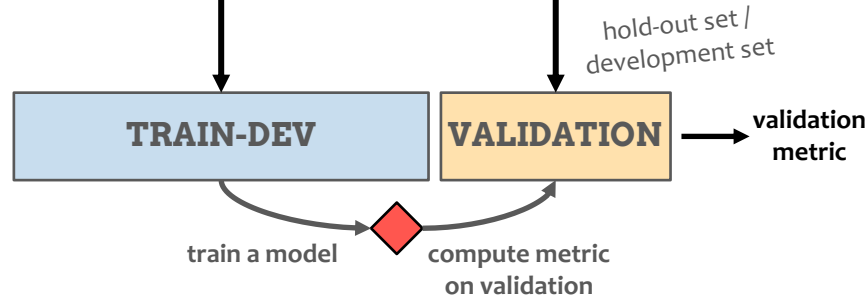
- 1** Split your data into train, validation, and test sets



- 2** For each hyperparameter combination  $\varphi_i \in \Psi$

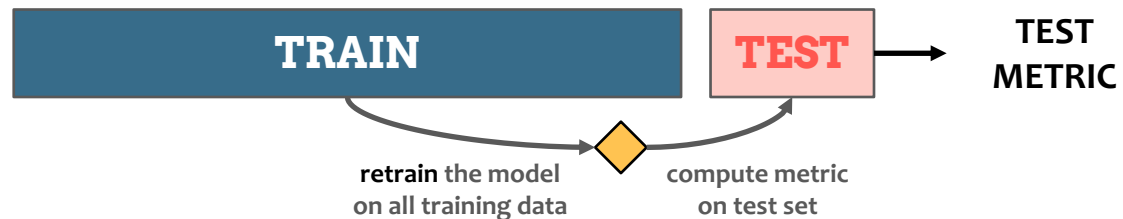
A	B
1	9
3	14
4	12
8	18
12	20

hyperparameters



- 3** Choose the hyperparameter combination with the best metric

$\varphi^*$ : A **1** **18** B



# Holdout Strategy

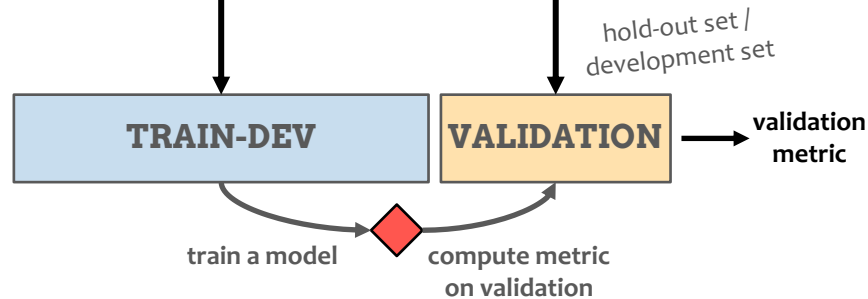
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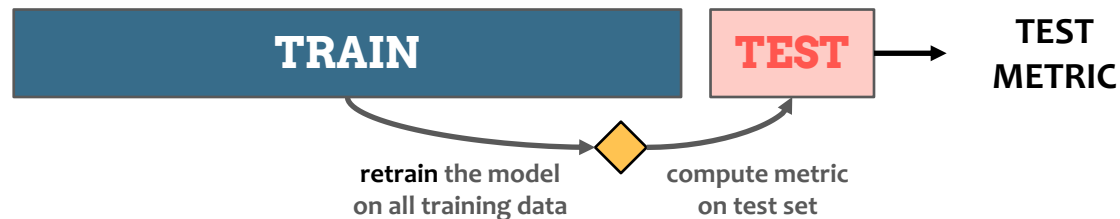
hyperparameters



You can use **stratified sampling** if you want.

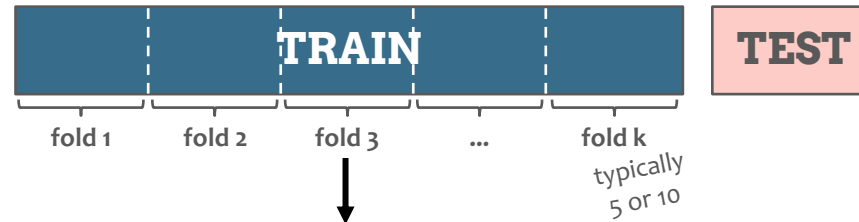
**3** Choose the hyperparameter combination with the best metric

$\varphi^*$ : A **1** **18** B



# k-Fold Strategy

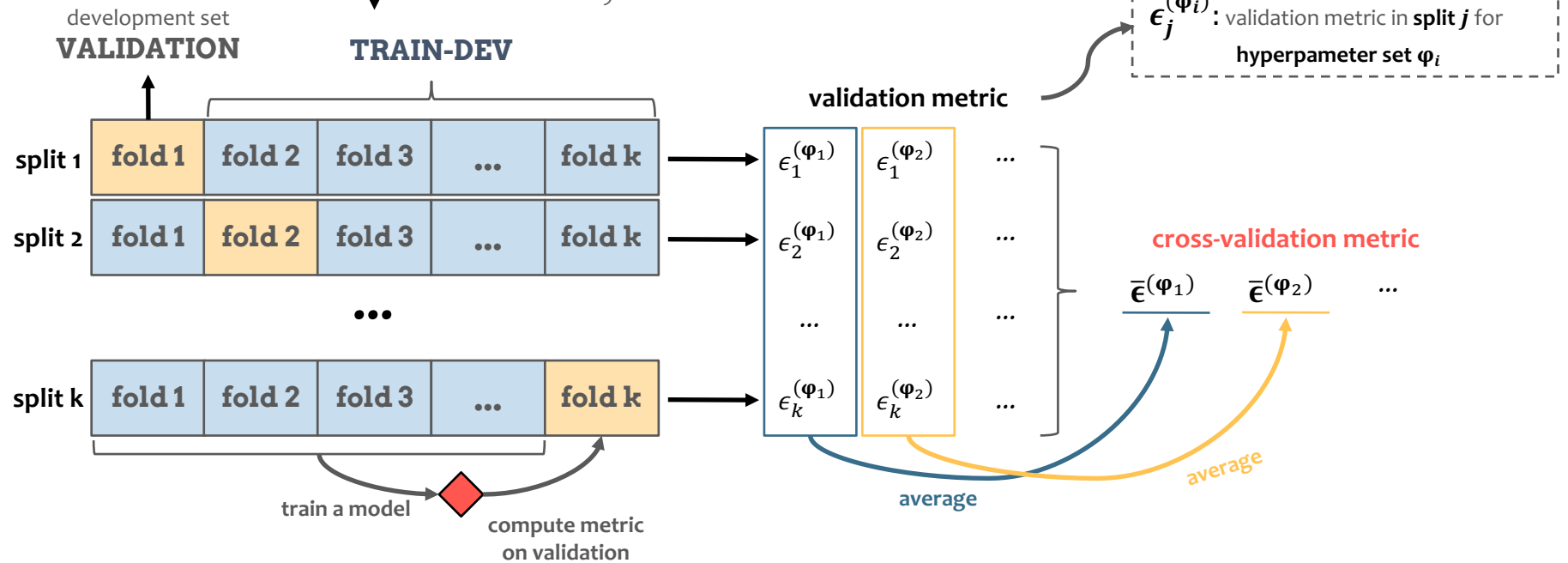
**1** Set aside the test set and split the train set into  $k$  folds



**2** For each hyperparameter combination  $\varphi_i \in \Psi$

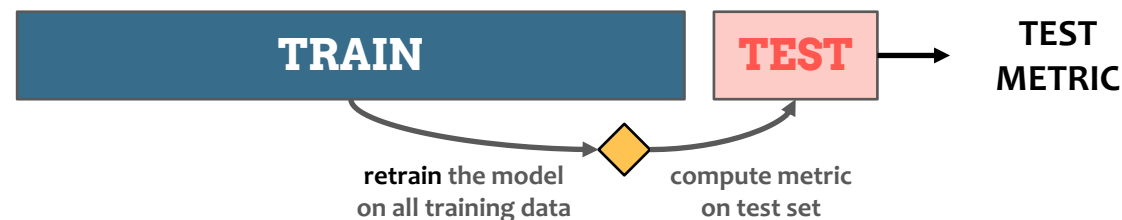
A	B
1	9
3	14
4	12
8	18
12	20

hyperparameters



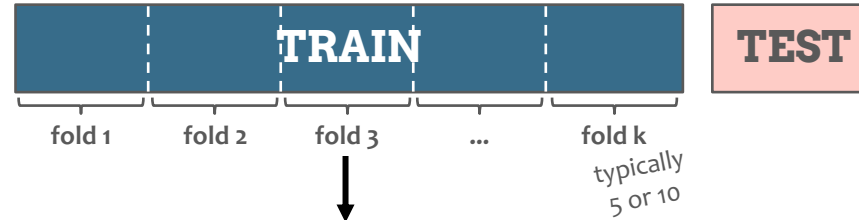
**3** Choose the hyperparameter combination with the best metric

$\varphi^*$ : A **1** **18** B



# k-Fold Strategy

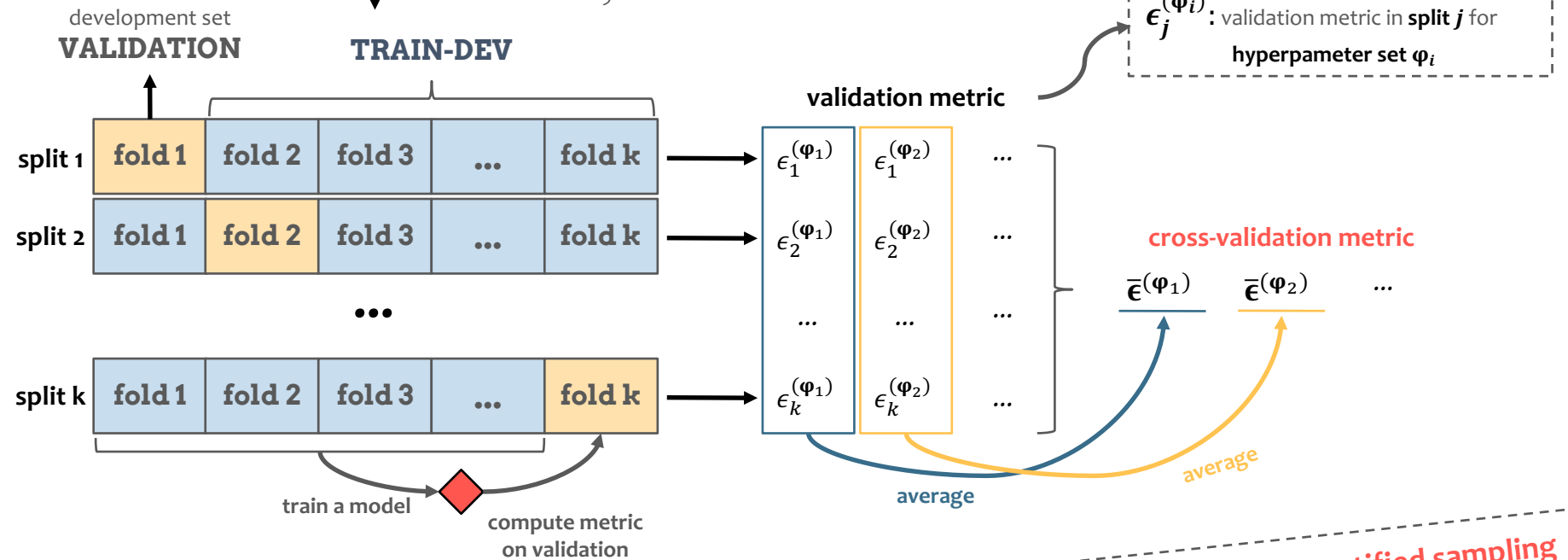
**1** Set aside the test set and split the train set into  $k$  folds



**2** For each hyperparameter combination  $\varphi_i \in \Psi$

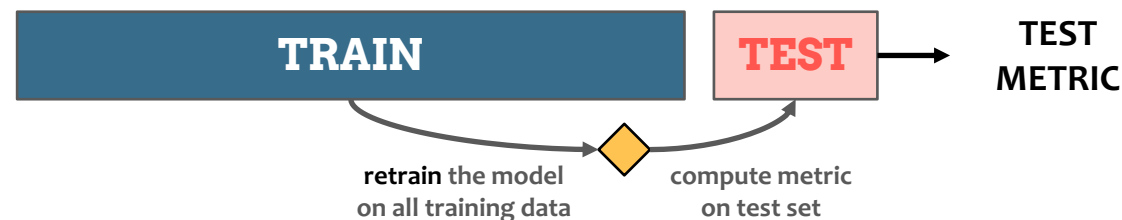
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hyperparameters



**3** Choose the hyperparameter combination with the best metric

$\varphi^*$ : A **1** **18** B



 You can use **stratified sampling** if you want.

# **Search Space for Fine-Tuning**

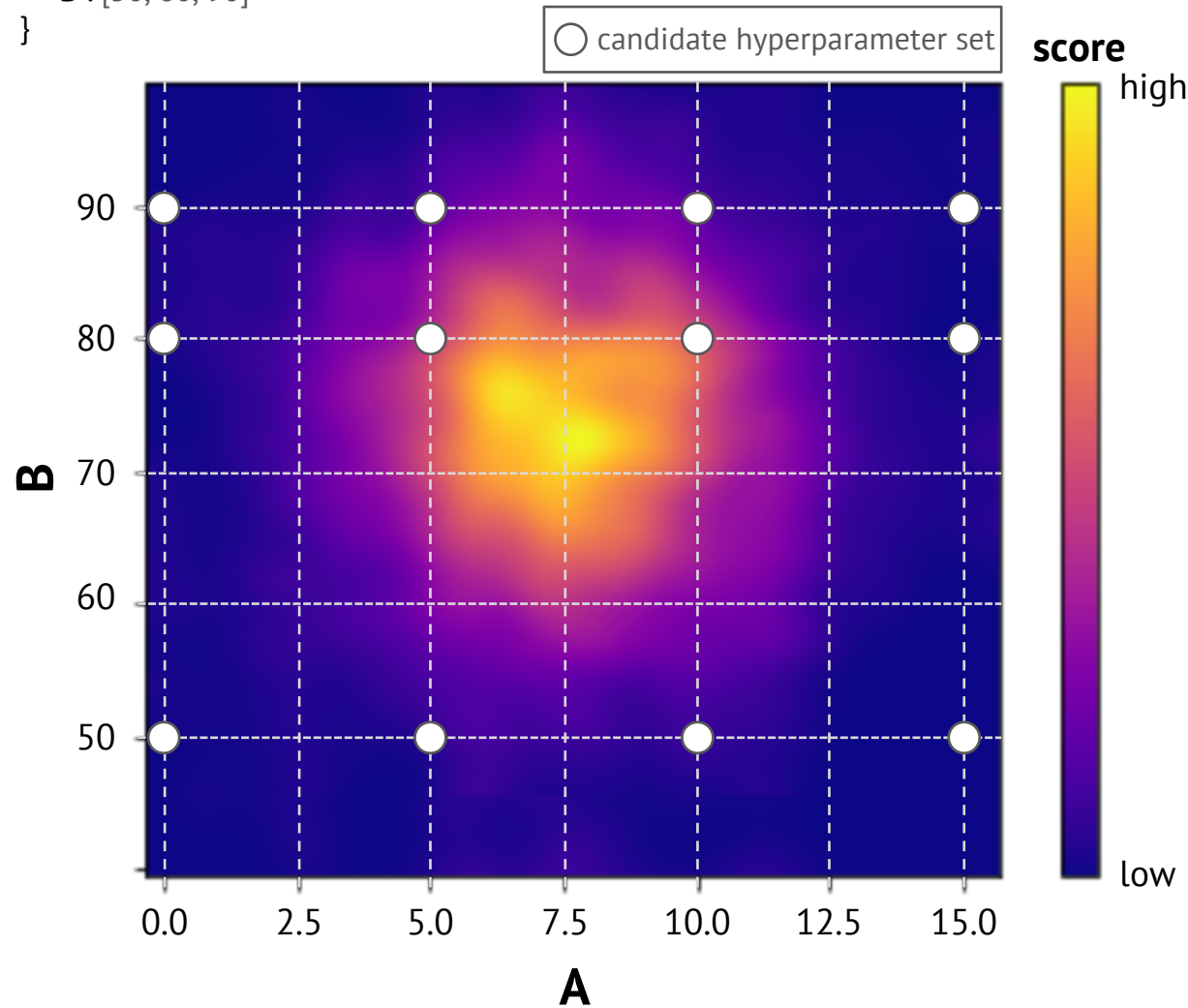
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# Grid Search

`sklearn.model_selection.GridSearchCV`

hyperparameters  
**search space** = {  
  'A': [0.0, 5.0, 10.0, 15.0],  
  'B': [50, 80, 90]  
}



The **search space** may not include the optimum hyperparameter combination: the highest score (lowest error).



The larger the **search space**, the longer (exponentially) the grid search.

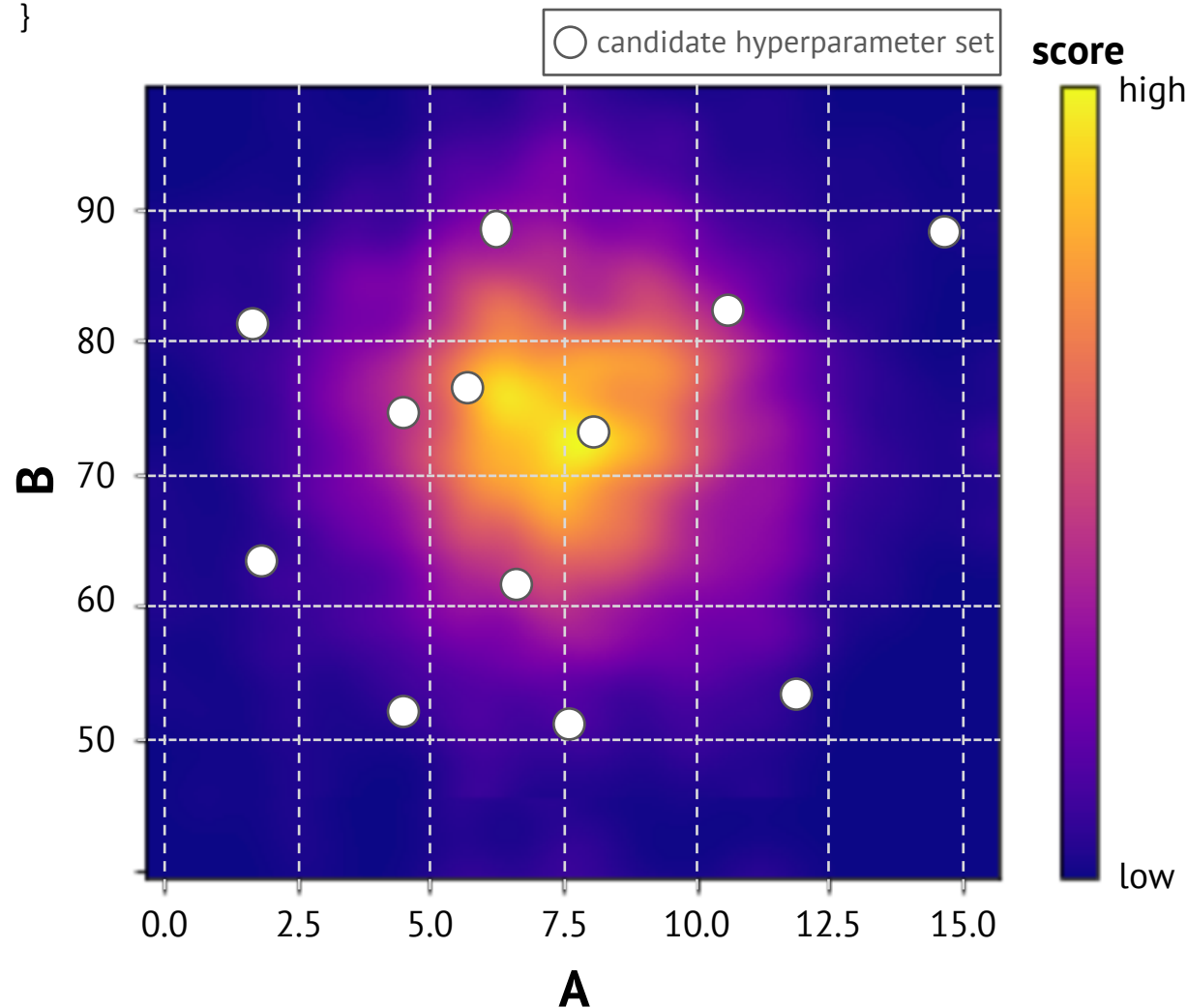
# Randomized Search

n = 9

search space = {

hyperparameters  
'A': [0.0, 0.25, 0.5, ..., 14.75, 15.0],  
'B': [50, 51, 52, ..., 86, 87, 88, 89, 90]  
}

`sklearn.model_selection.RandomizedSearchCV`



You can even increase the  
**hyperparameter distribution** for  
fine-tuning and keep **a feasible**  
**processing time.**

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