# AutoML: Beyond AutoML

## Per-Instance Algorithm Configuration

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# Homogeneous vs. Heterogeneous Instances

## Assumption of AC: Homogeneous Instance Distribution

- Algorithm configuration tools assume that the instance distribution is homogeneous (see video on "Best Practices for AC")
- Important because
  - there is a well-performing configuration for all (or most) instances
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$\rightsquigarrow$ What should we do with heterogeneous instance distributions?

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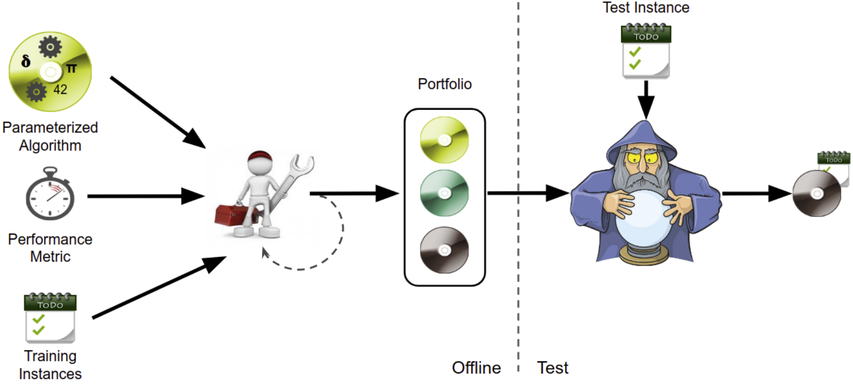
2. We don't want to do algorithm configuration always from scratch
3. An adaptive configuration system would be the holy grail

    $\leadsto$ hard to achieve

# PIAC: Per-Instance Algorithm Configuration



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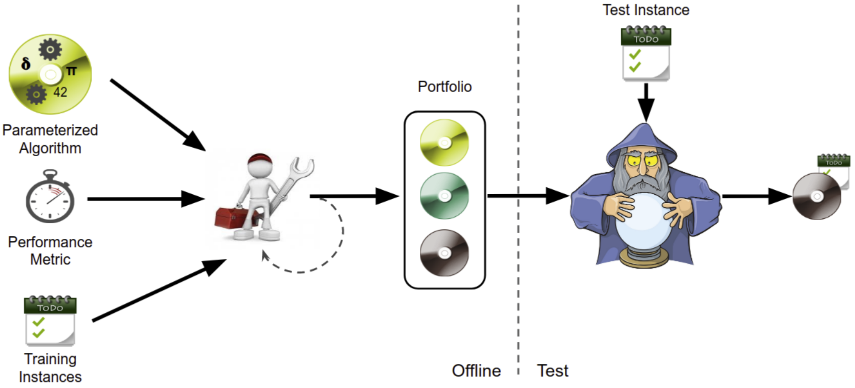


- You can use whichever kind of algorithm selection (wizard) you want
- Challenge: Building a portfolio
- Use case: Instances are heterogeneous

# PIAC: Manual Expert Approach

## Basic Assumption

Heterogeneous instance set can be divided into homogeneous subsets

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## Manual Expert

- An expert knows the homogeneous subsets (e.g., origin of instances)
- Determine a well-performing configuration on each subset
  $\rightarrow$ portfolio of configurations
- Use Algorithm Selection to select a well-performing configuration on each instance

# Instance-Specific Algorithm Configuration: ISAC [Kadioglu et al. 2010]

## Idea

Training:

1. Cluster instances into homogeneous subsets
(using $g$-means in the instance feature space)
2. Apply algorithm configuration (here GGA) on each instance set

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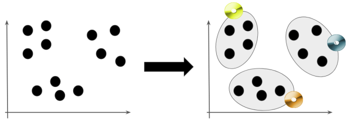
Test:

1. Determine the nearest cluster ($k$-NN with $k = 1$) in feature space
2. Apply optimized configuration of this cluster



# Hydra [Lin et al. 2010]

## Idea

- Iteratively add configurations to a portfolio $\mathbf{P}$, start with $\mathbf{P} = \emptyset$
- In each iteration, determine configuration that is complementary to $\mathbf{P}$
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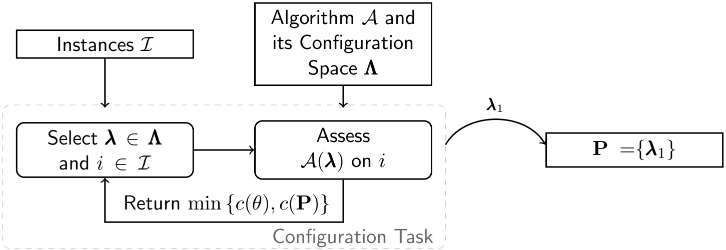

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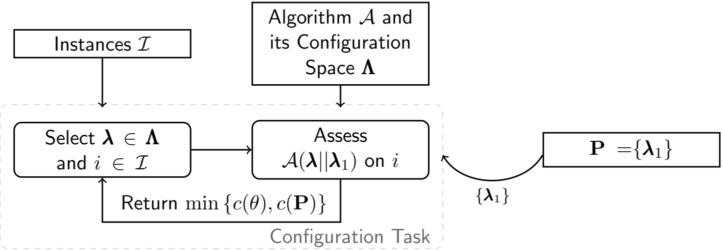

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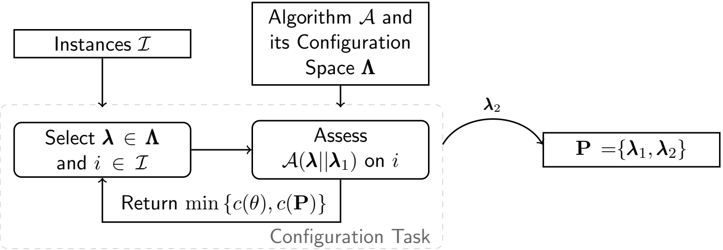

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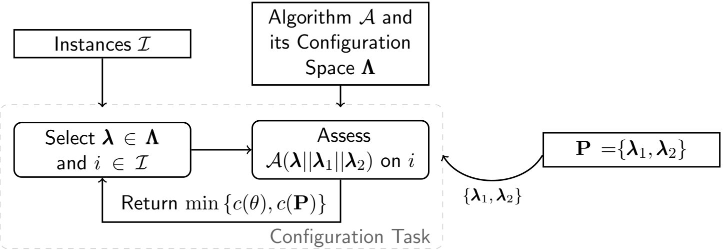
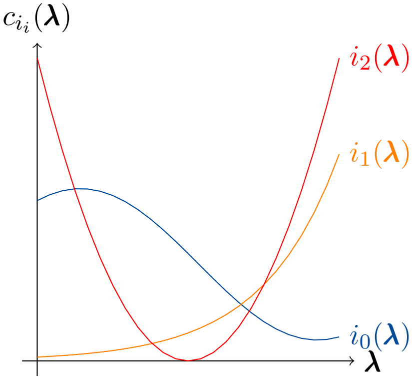


# Heterogeneous example



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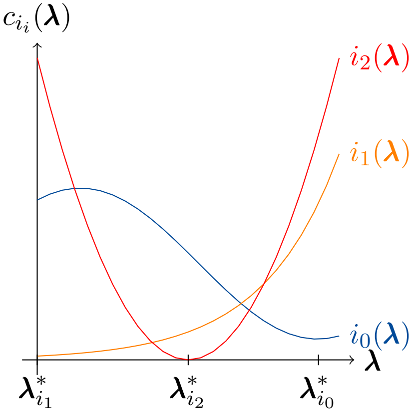

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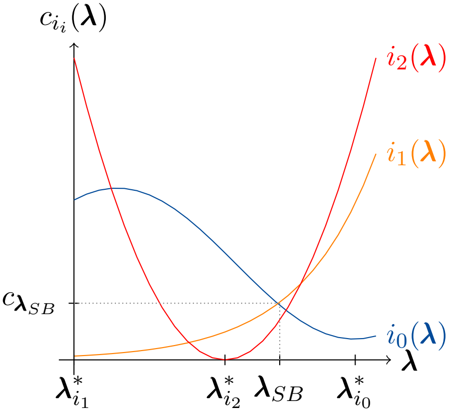

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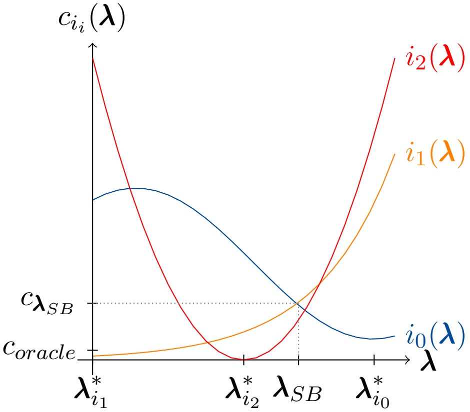
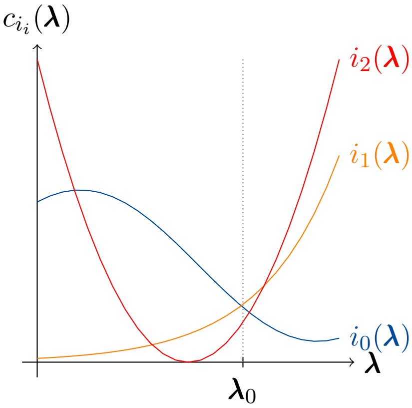


# Hydra: Iteration 1




Search initial well performing configuration. Add $\boldsymbol{\lambda}_0$ to $\mathbf{P}$

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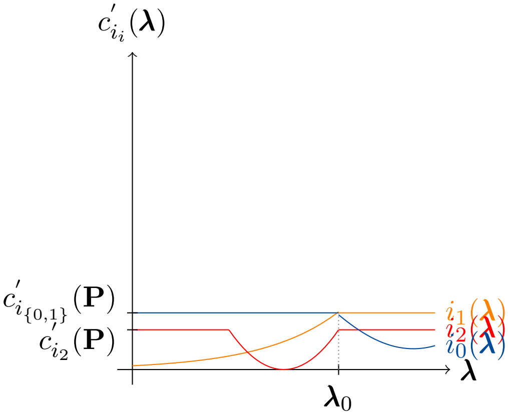
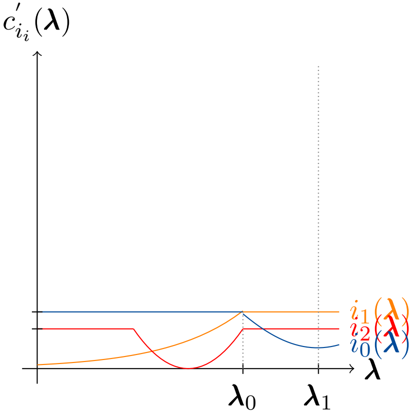


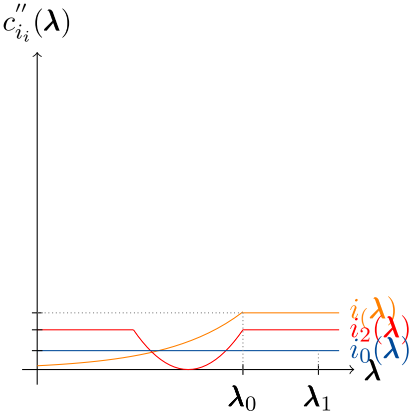

Update metric

# Hydra: Iteration 2




Search well performing configuration complementary to $\mathbf{P}$.
Add $\boldsymbol{\lambda}_1$ to $\mathbf{P}$.

# Hydra: Iteration 2

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- In each iteration, only optimize on instances not solved so far
- The time slot is a further parameter in the configuration space
- Optimize marginal contribution per time spent:

$$\frac{c(\mathcal{S}) - c(\mathcal{S} \oplus \langle \boldsymbol{\lambda}, t \rangle)}{t}$$

# Submodularity

## Observation

- Performance metrics of Hydra and Cedalion are submodular
  - Family of functions
  - Adding an element to a set reduces the function value
  - Diminishing returns: decrease of the value reduction over time

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## Definition (Submodularity of $f$)

For every $X, Y \subseteq Z$ with $X \subseteq Y$ and every $x \in Z - Y$ we have that
$f(X \cup \{x\}) - f(X) \geq f(Y \cup \{x\}) - f(Y)$

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## Advantage

We can bound the error of the portfolio/schedule:
At most away from optimum by factor of $0.63$ (see [Streeter & Golovin '08])

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3. Update clusters based on performance (estimates)
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- increase the configuration budget in each iteration
  - first clusterings will have a poor quality $\rightarrow$ small configuration time
  - later clusterings will be better $\rightarrow$ more configuration time