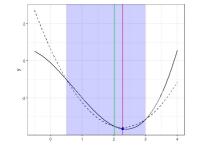
# **Optimization in Machine Learning**

# Univariate optimization Brent's method





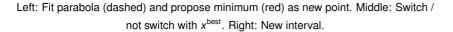
#### Learning goals

- Quadratic interpolation
- Brent's procedure

Similar to golden ratio procedure but select  $x^{\text{new}}$  differently:  $x^{\text{new}}$  as minimum of a parabola fitted through



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### **QUADRATIC INTERPOLATION COMMENTS**

- Quadratic interpolation **not robust**. The following may happen:
  - Algorithm suggests the same x<sup>new</sup> in each step,
  - x<sup>new</sup> outside of search interval,
  - Parabola degenerates to line and no real minimum exists
- Algorithm must then abort, finding a global minimum is not guaranteed.



#### **BRENT'S METHOD**

- Brent proposed an algorithm (1973) that alternates between golden ratio search and quadratic interpolation as follows:
  - Quadratic interpolation step acceptable if: (i) x<sup>new</sup> falls within [x<sup>left</sup>, x<sup>right</sup>] (ii) x<sup>new</sup> sufficiently far away from x<sup>best</sup> (Heuristic: Less than half of movement of step before last)
  - Otherwise: Proposal via golden ratio
- Benefit: Fast convergence (quadratic interpolation), unstable steps (e.g. parabola degenerated) stabilized by golden ratio search
- Convergence guaranteed if the function *f* has a local minimum
- Used in R-function optimize()



#### **EXAMPLE: MLE POISSON**

- Poisson density:  $f(k \mid \lambda) := \mathbb{P}(x = k) = \frac{\lambda^k \cdot \exp(-\lambda)}{k!}$
- Negative log-likelihood for *n* observations:

$$-\ell(\lambda,\mathcal{D}) = -\log \prod_{i=1}^{n} f\left(x^{(i)} \mid \lambda\right) = -\sum_{i=1}^{n} \log f\left(x^{(i)} \mid \lambda\right)$$

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GR and Brent converge to minimum at  $x^* \approx 1$ .

**But:** GR needs  $\approx$  45 it., Brent only needs  $\approx$  15 it. for same tolerance.