



# NOISE-RESILIENT VARIATIONAL HYBRID QUANTUM- CLASSICAL OPTIMIZATION

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- $|\psi(\theta^{opt})\rangle$  best approximation of the ground state



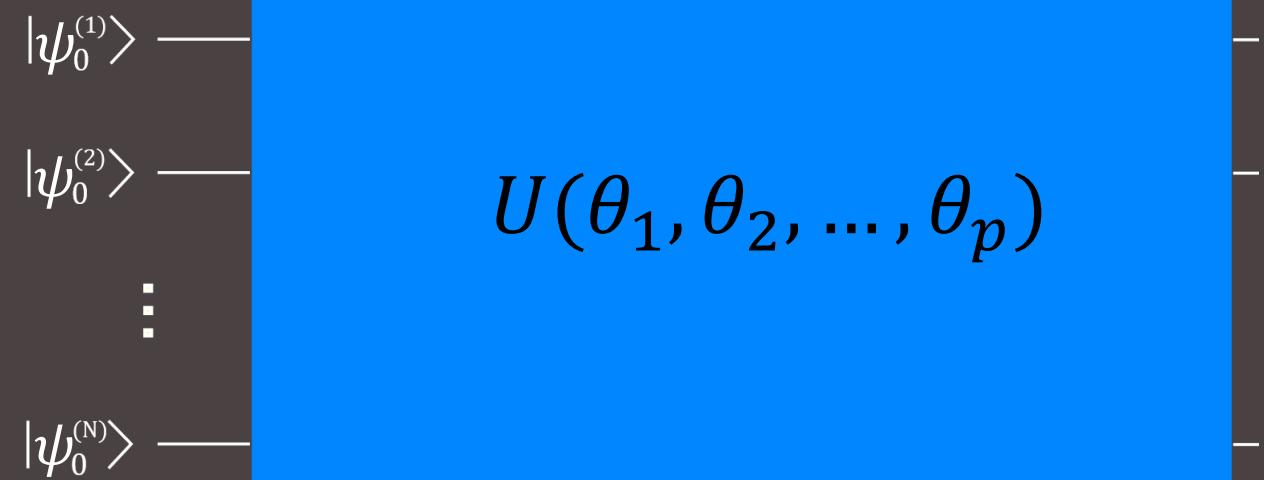
# Variational method and Hybrid approach



## Variational method and Hybrid approach

Quantum

- $|\psi(\theta)\rangle = U(\theta)|\psi_0\rangle$

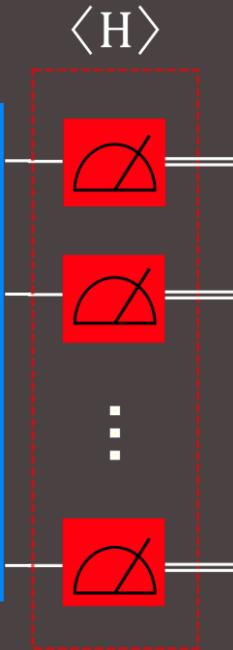




# Variational method and Hybrid approach

$|\psi_0^{(1)}\rangle$  —  
 $|\psi_0^{(2)}\rangle$  —  
⋮  
 $|\psi_0^{(N)}\rangle$  —

$$U(\theta_1, \theta_2, \dots, \theta_p)$$

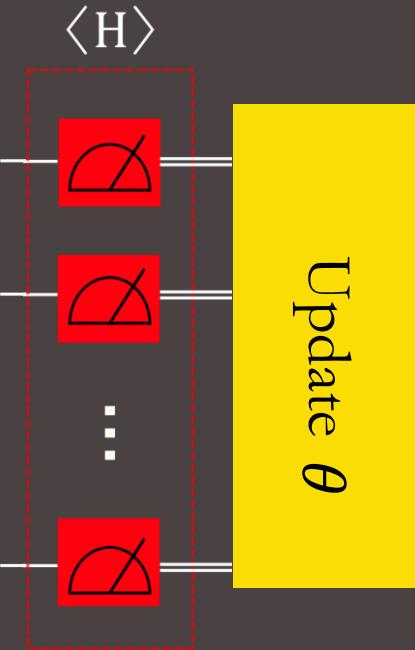
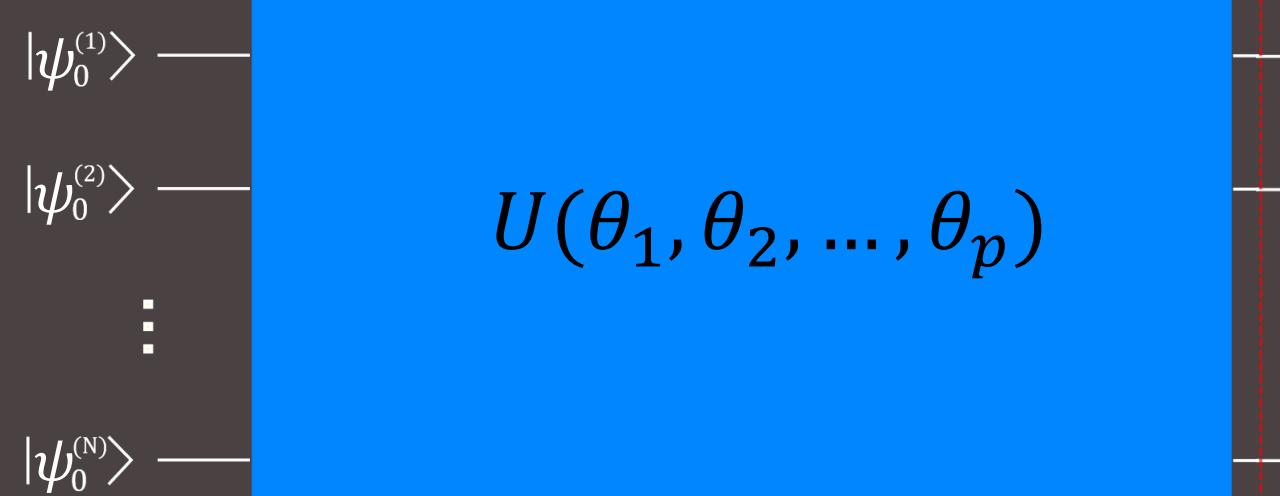


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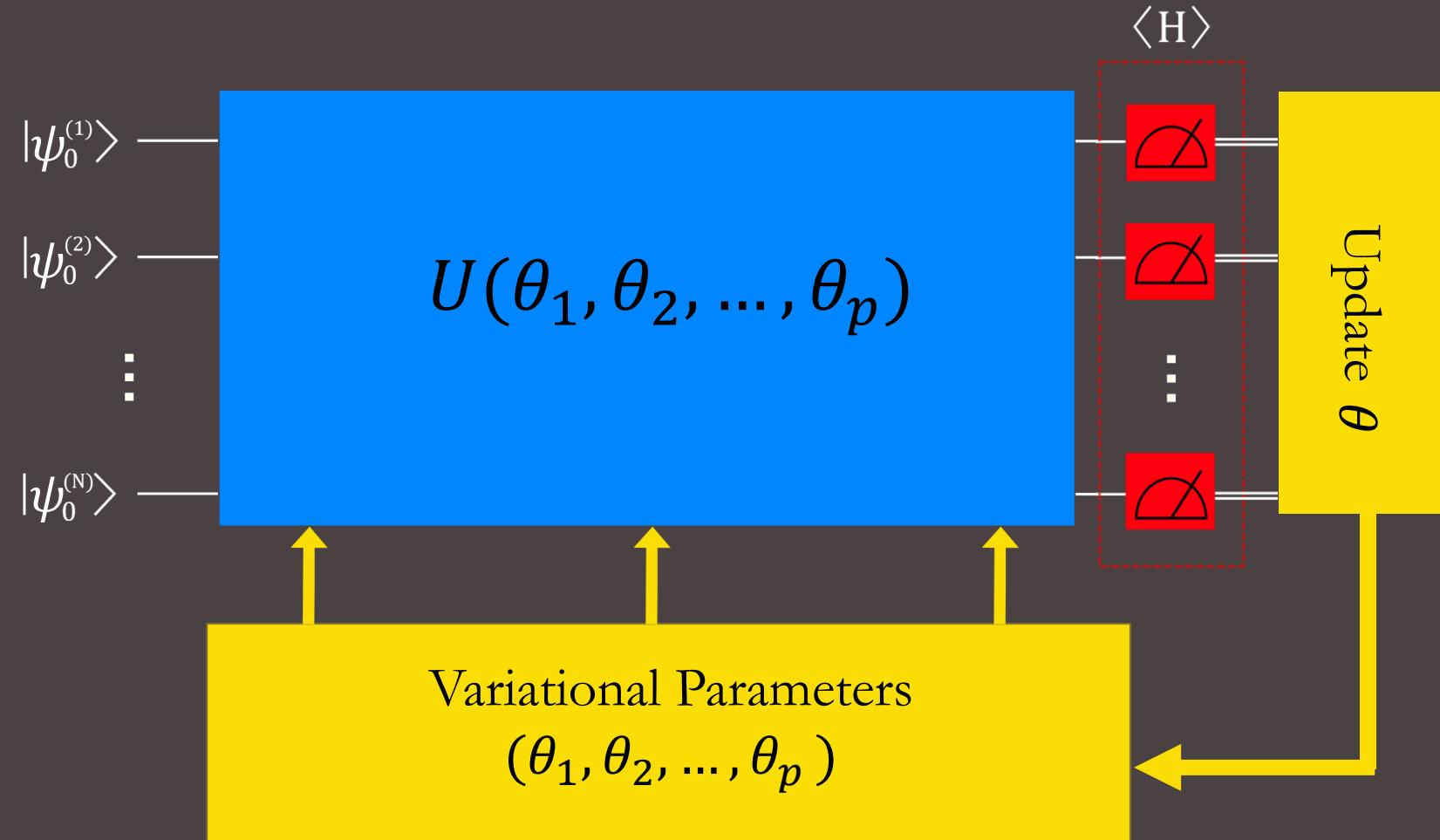
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Classical

- Perform a  
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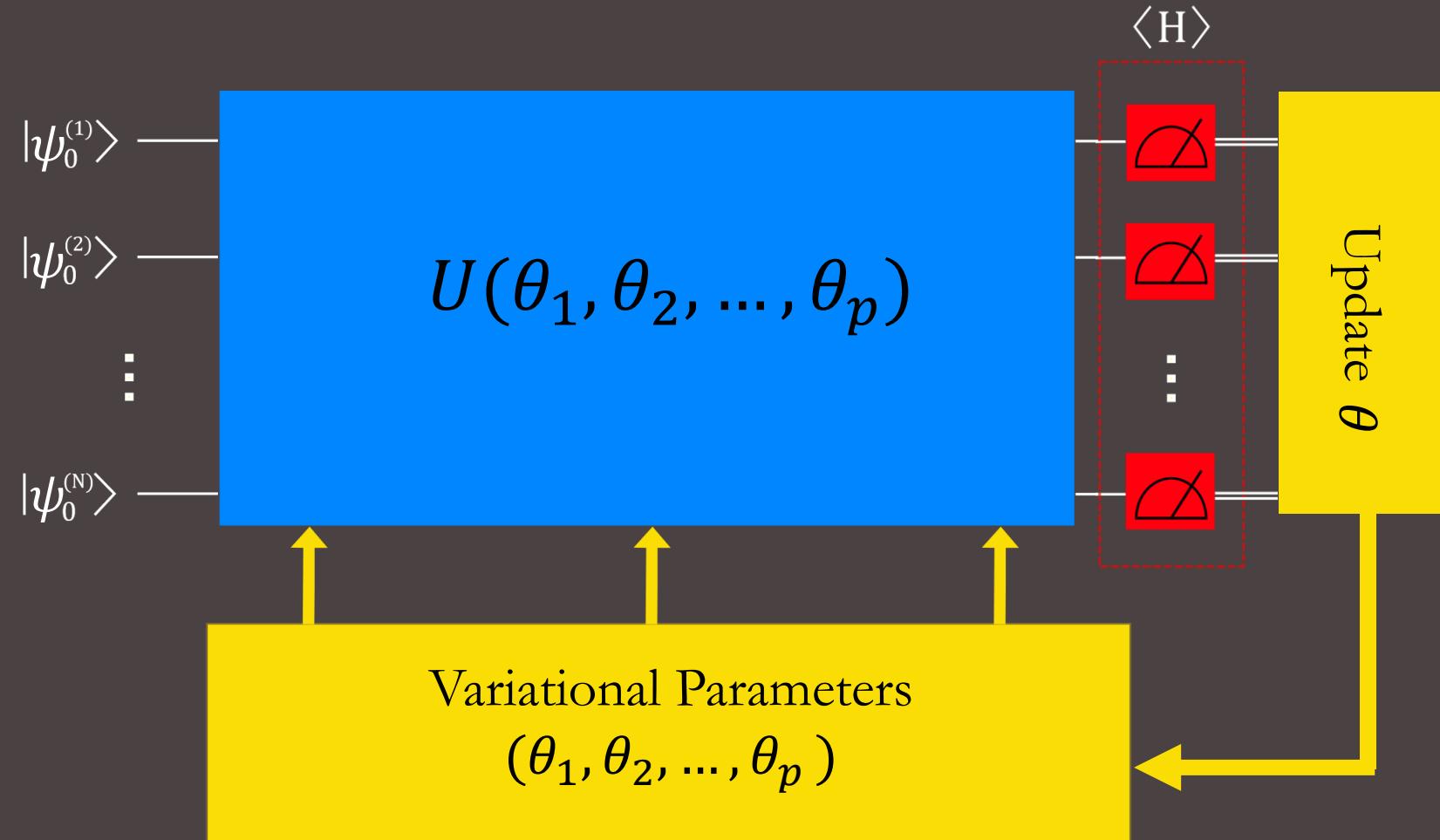
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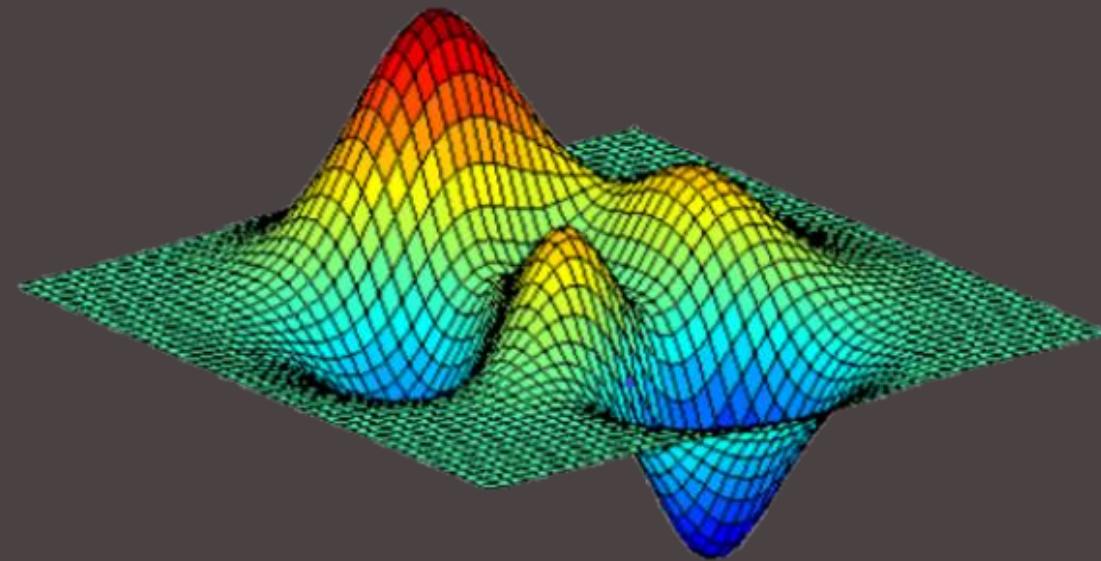
Find  $\theta^{opt}$ !



## Role of $\theta$ 's and optimization landscape

- ▶  $\theta$  define a parameter space

$C(\theta) \rightarrow$  landscape



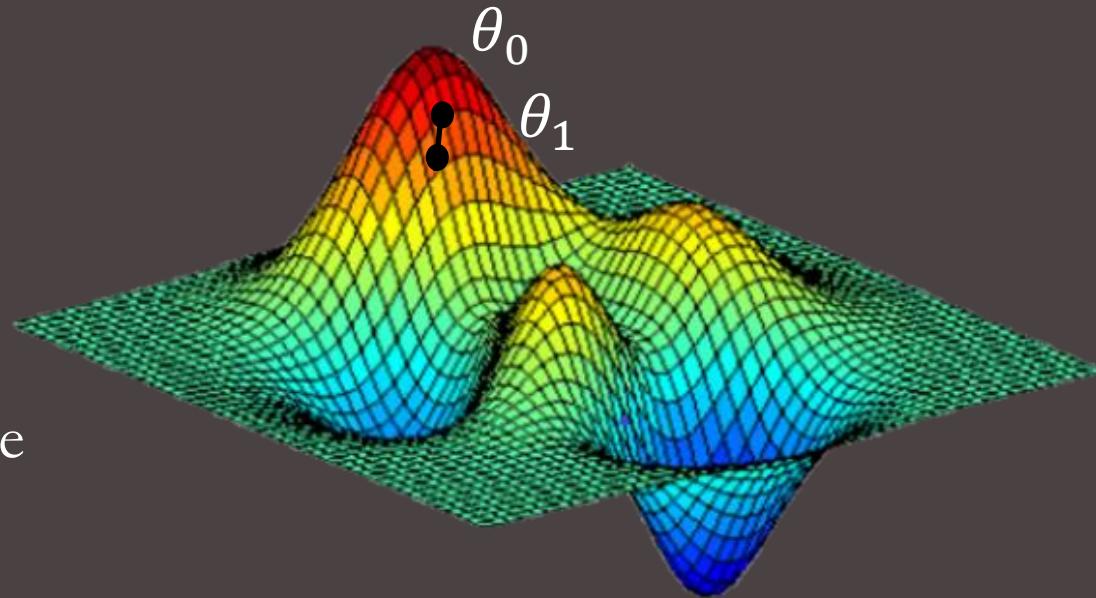


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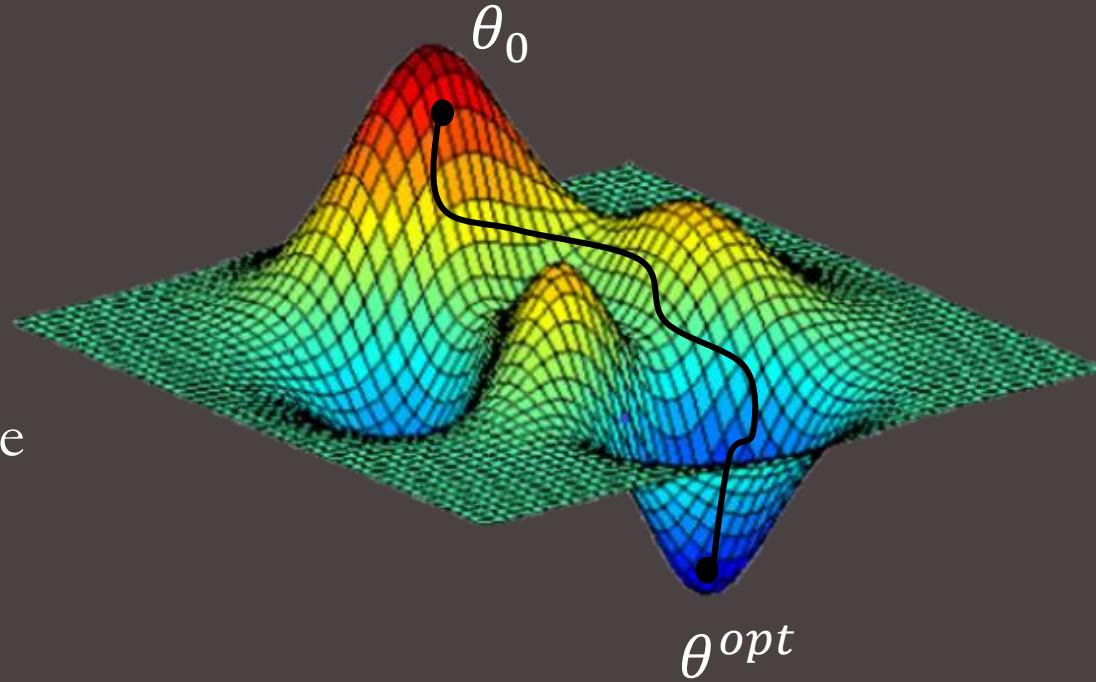


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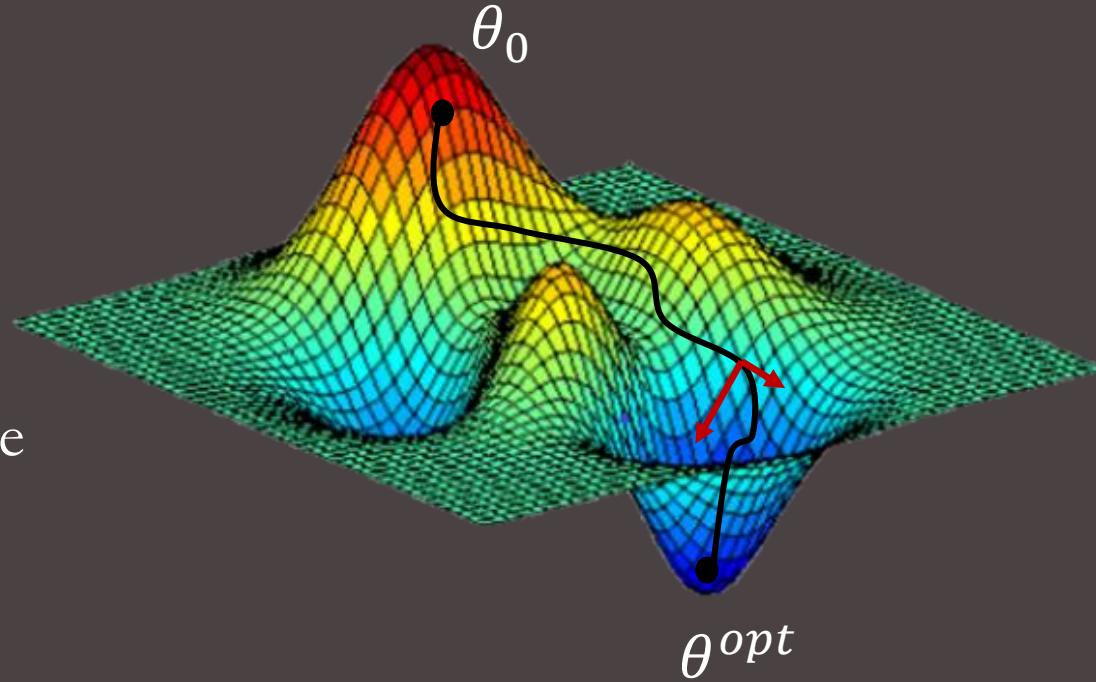


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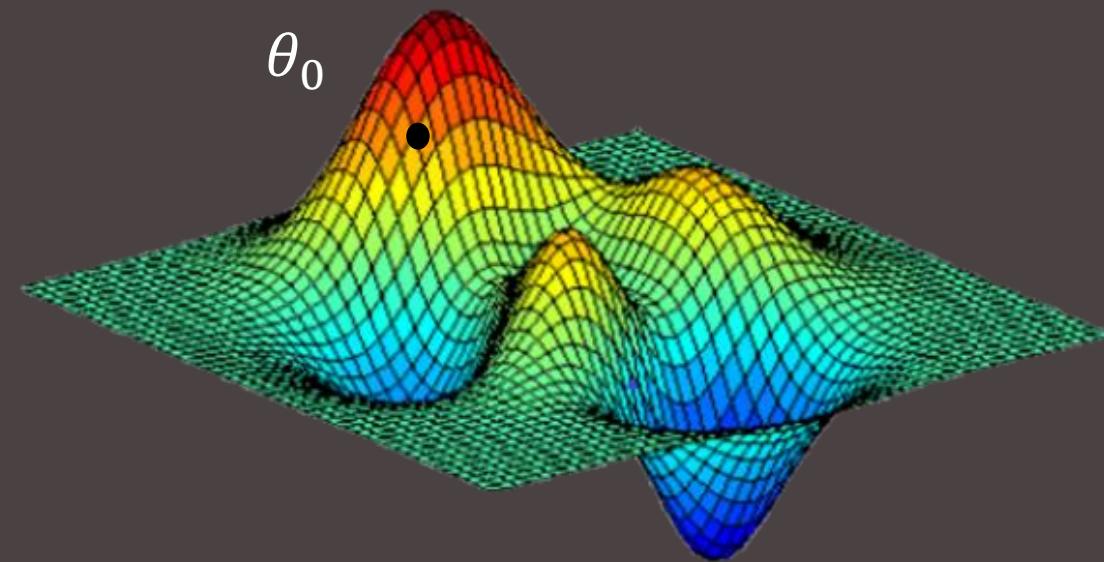
- ▶ At each optimization step we move a little
- ▶ The algorithm define a *path*...
- ▶ And the gradient is algorithm's compass!





# Stochastic Optimization and Noise

- ▶ Path full of traps

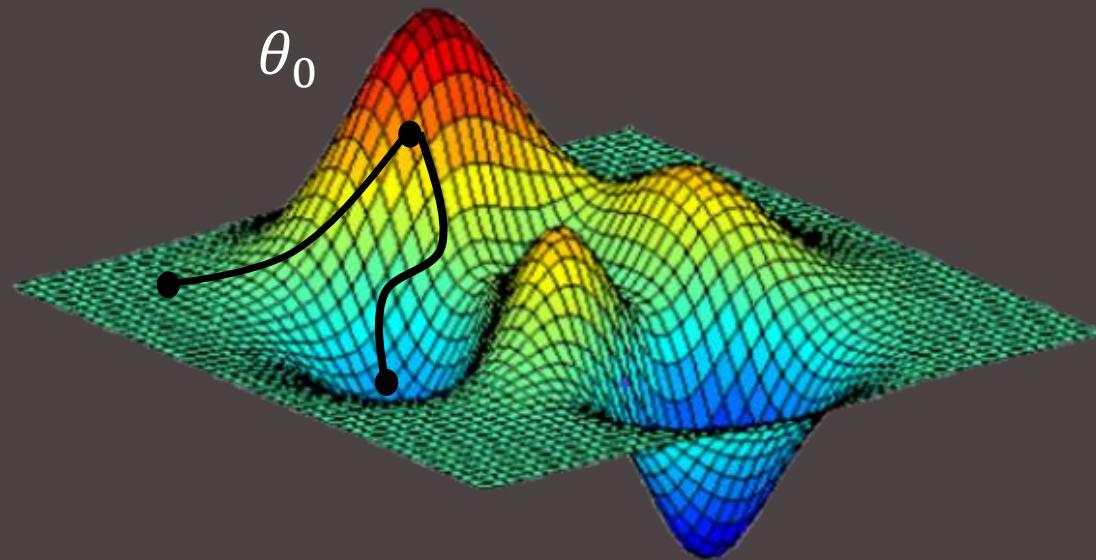




# Stochastic Optimization and Noise

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- ▶ Local minima or Plateaus

$$\nabla_{\theta} C = 0$$



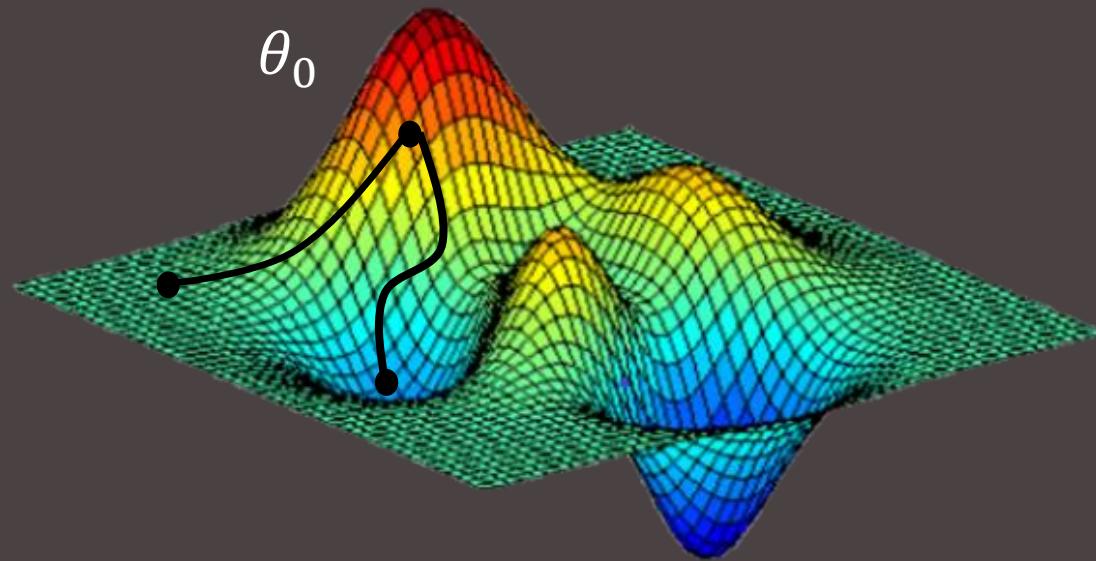


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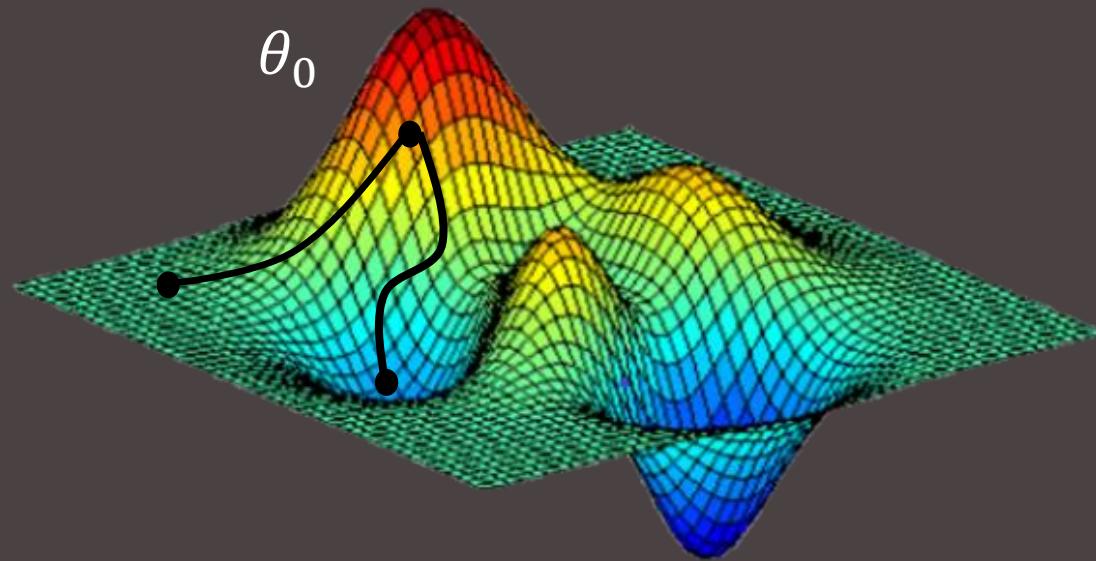


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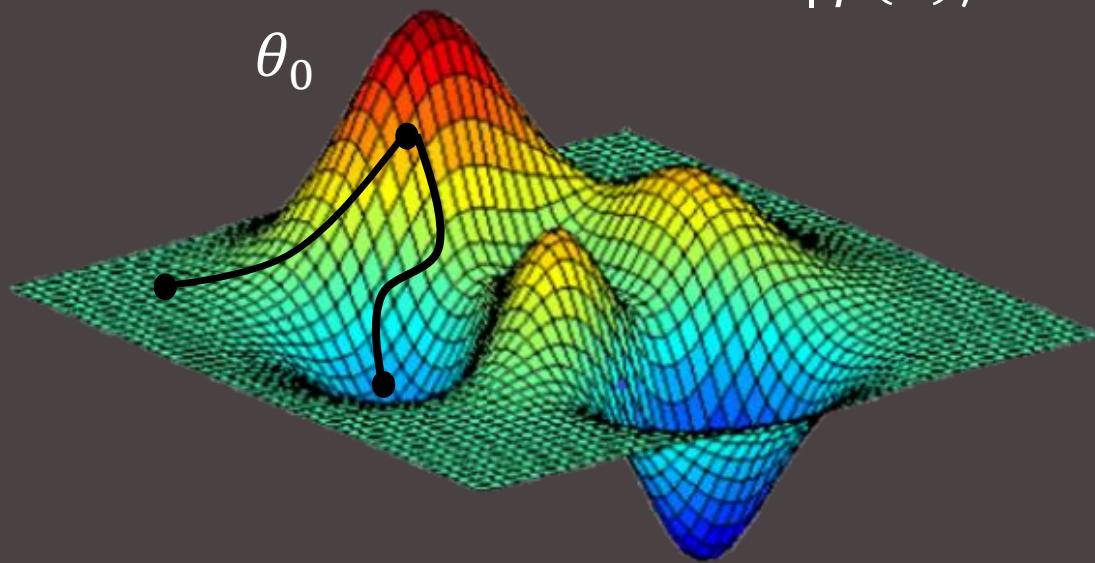
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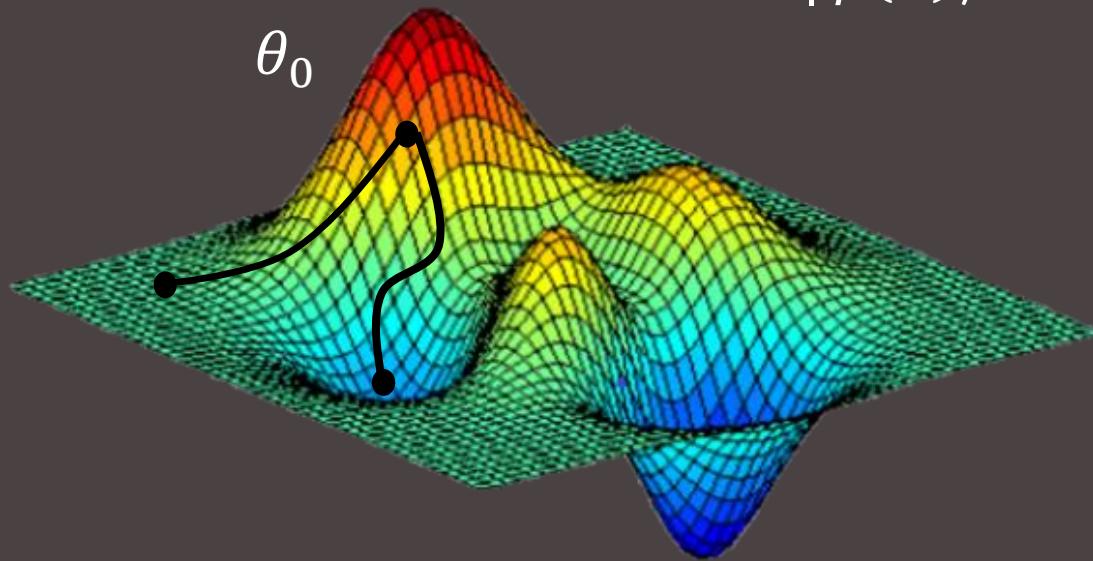
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Convergence  
Role of Noise and outcomes } geometrical point of view?



# Quantum Fisher Information bound

$$C_{noisy}(\theta^{[1:I]}) - C(\theta^{opt}) \leq Err(\theta^{opt}, \vartheta^{opt}) + \frac{R\sqrt{p}\|H\|_\infty}{\sqrt{I}} \max_{j,\theta} \sqrt{\text{QFI}_j(\theta)}$$



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Increases with noise strength



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Decreases with noise strength

Tradeoff → Noise can help to explore parameter space AND to bound the error

Contact me at

[laura.gentini@unifi.it](mailto:laura.gentini@unifi.it)

Or

Visit our group site

<https://qtif.weebly.com/>

(Work in progress,  
Come back soon!)



THANK YOU