

Title: Adiabatic quantum optimization fails for random instances of NP-complete problems

Date: Oct 07, 2009 04:00 PM

URL: <http://pirsa.org/09100099>

Abstract: Adiabatic quantum optimization has attracted a lot of attention because small scale simulations gave hope that it would allow to solve NP-complete problems efficiently. Later, negative results proved the existence of specifically designed hard instances where adiabatic optimization requires exponential time. In spite of this, there was still hope that this would not happen for random instances of NP-complete problems. This is an important issue since random instances are a good model for hard instances that can not be solved by current classical solvers, for which an efficient quantum algorithm would therefore be desirable. Here, we will show that because of a phenomenon similar to Anderson localization, an exponentially small eigenvalue gap appears in the spectrum of the adiabatic Hamiltonian for large random instances, very close to the end of the algorithm. This implies that unfortunately, adiabatic quantum optimization also fails for these instances by getting stuck in a local minimum, unless the computation is exponentially long.

Joint work with Boris Altshuler and Hari Krovi

Adiabatic quantum optimization and Anderson localization

Jérémie Roland

Joint work with:
Boris Altshuler
Hari Krovi

October 7, 2009



**NEC Laboratories
America**
Relentless passion for innovation



Why quantum computing?

Quantum computing provides speed-up for specific problems

- Factoring
- Discrete logarithms
- Simulation of quantum mechanics
- etc...

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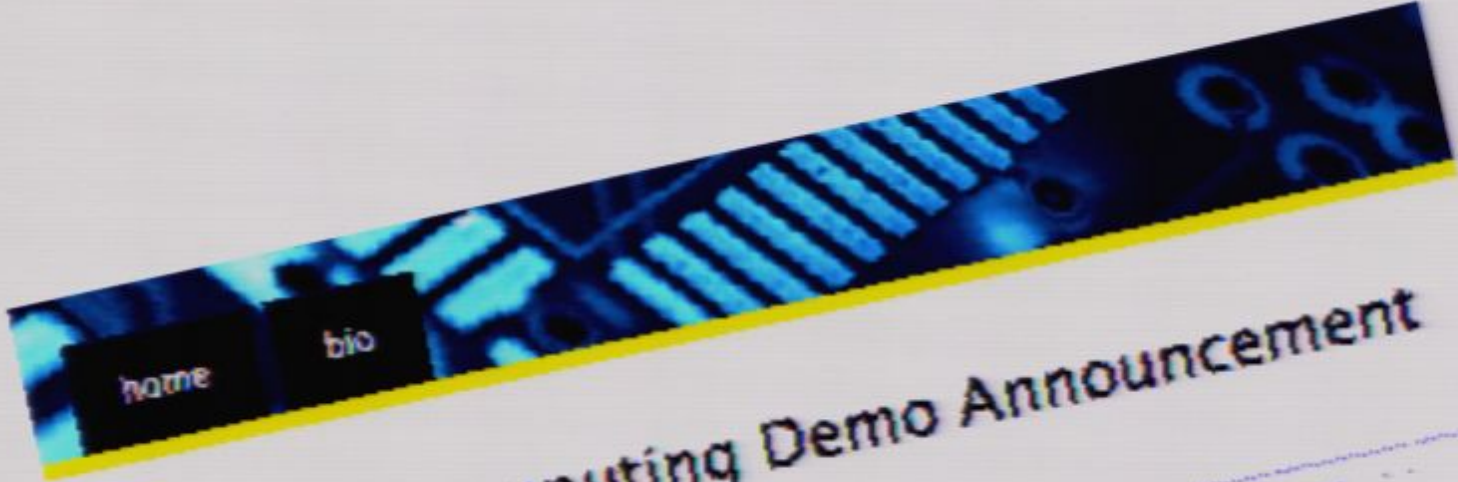
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What about NP-complete problems?

- 3-SAT:

$$(x_1 \vee \bar{x}_2 \vee x_5) \wedge (\bar{x}_1 \vee x_3 \vee \bar{x}_5) \wedge (\bar{x}_2 \vee x_4 \vee x_5)$$



Quantum Computing Demo Announcement

January 19, 2007

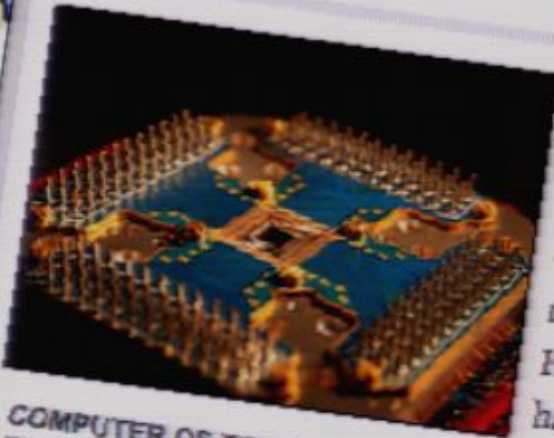
SCIENTIFIC AMERICAN

February 13, 2007 | 0 comments

First "Commercial" Quantum Computer Solves Sudoku Puzzles

Quantum computing company banks on a long-shot form of quantum computing

By JR Minkel



COMPUTER OF TOMORROW
D-Wave Systems, a Canadian
company, has announced

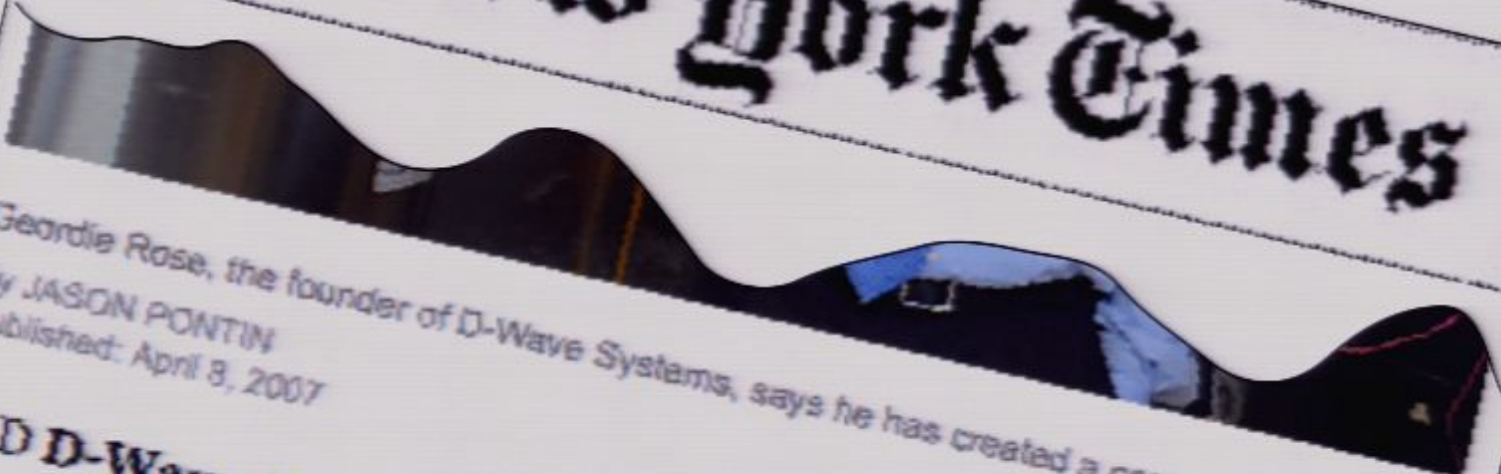
A Canadian firm today unveiled what it calls "the world's first commercially viable quantum computer." D-Wave Systems, Inc. announced the Quantum Computing Company's much ballyhooed rollout. History Museum has hailed the age of quantum computing as the dawn of the quantum age of computing.

The Economist

...y, near Venice
announced
On paper at least, quantum computers promise to reduce dramatically the time needed to solve a range of mathematical tasks known as NP-complete problems. One famous example is the travelling salesman problem—finding the shortest route between several cities. This is a puzzle that increases exponentially with the number of cities considered. The reason is that the number of possible routes grows exponentially with the number of cities. The first practical quantum computer was announced in 2001. It was able to solve a problem that would take a classical computer a billion years to solve. This is a puzzle that increases exponentially with the number of cities considered. The reason is that the number of possible routes grows exponentially with the number of cities. The first practical quantum computer was announced in 2001. It was able to solve a problem that would take a classical computer a billion years to solve.

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As it turns out quantum technology is particularly adept at tackling what are known in mathematics as "NP-complete" problems. NP stands for nondeterministic polynomial time, these are problems where the massive volume of computation and variables prevents a classical computer from solving them in a reasonable time. The reason is that the number of possible routes grows exponentially with the number of cities. The first practical quantum computer was announced in 2001. It was able to solve a problem that would take a classical computer a billion years to solve.

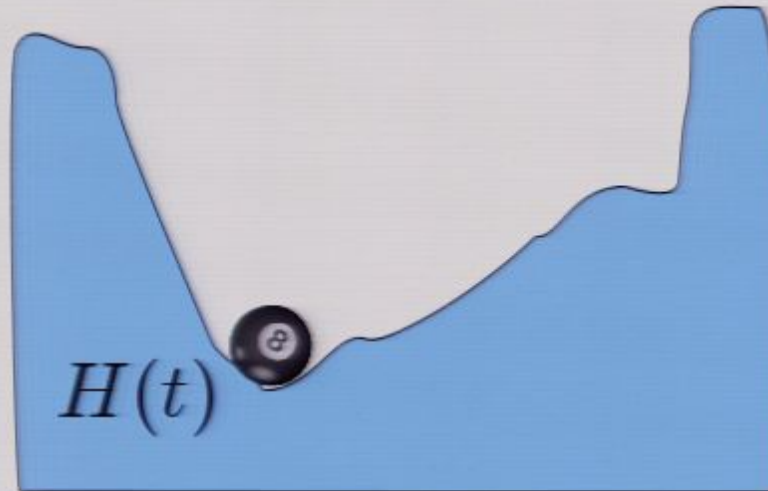
The New York Times



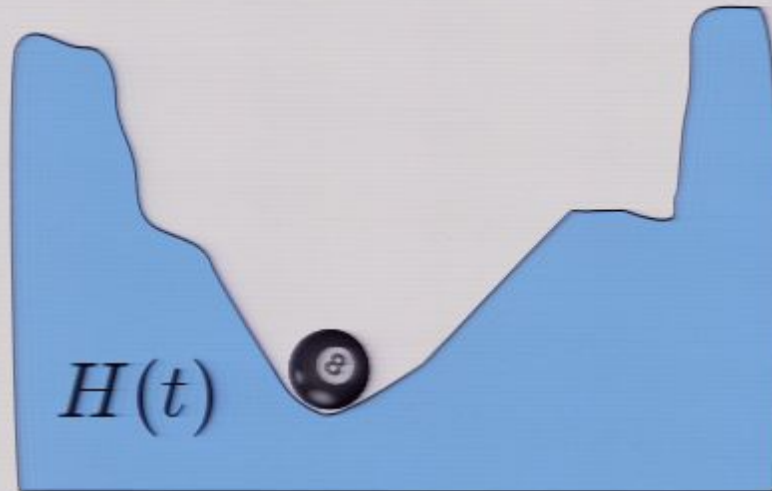
Geordie Rose, the founder of D-Wave Systems, says he has created a commercial quantum
By JASON PONTIN
Published: April 8, 2007

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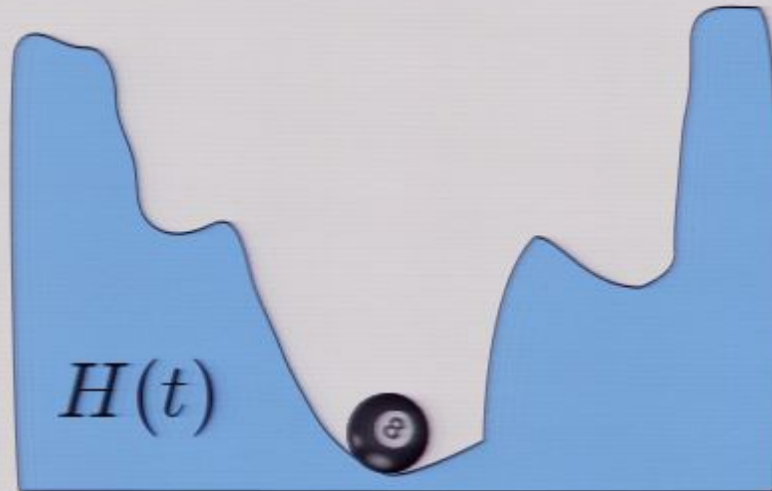
Adiabatic evolution



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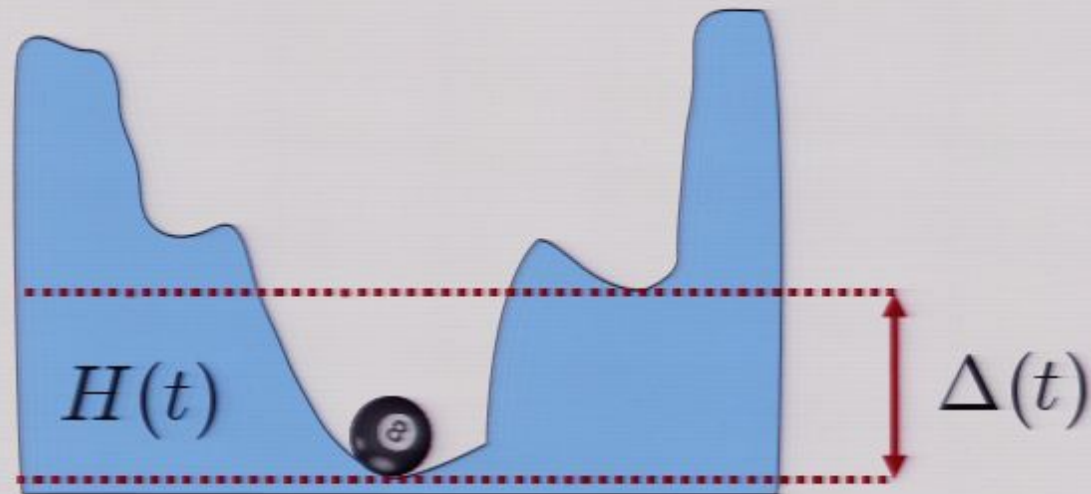


Adiabatic evolution



Slowly varying $H(t)$ \rightarrow Stays close to ground state

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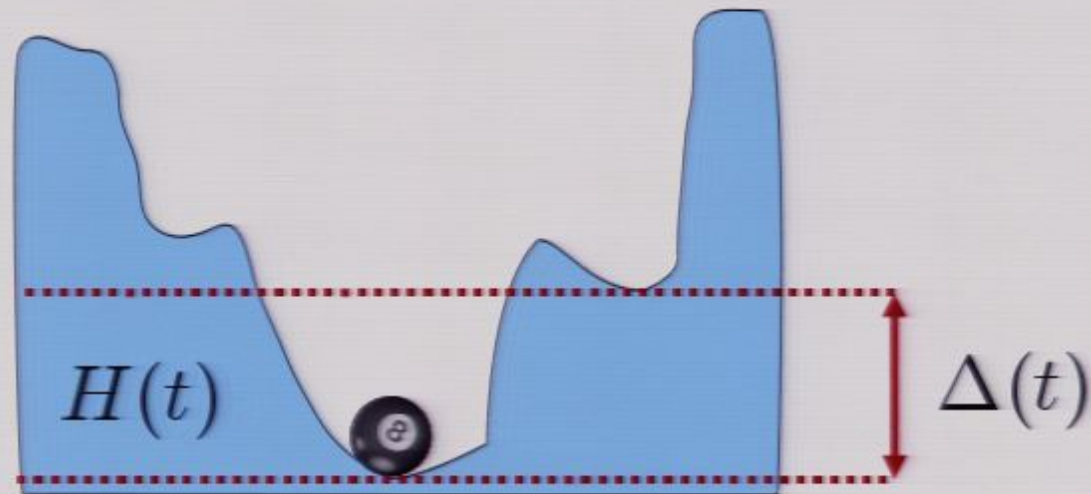


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Probability of excitation depends on

- Total time T (slower is better)
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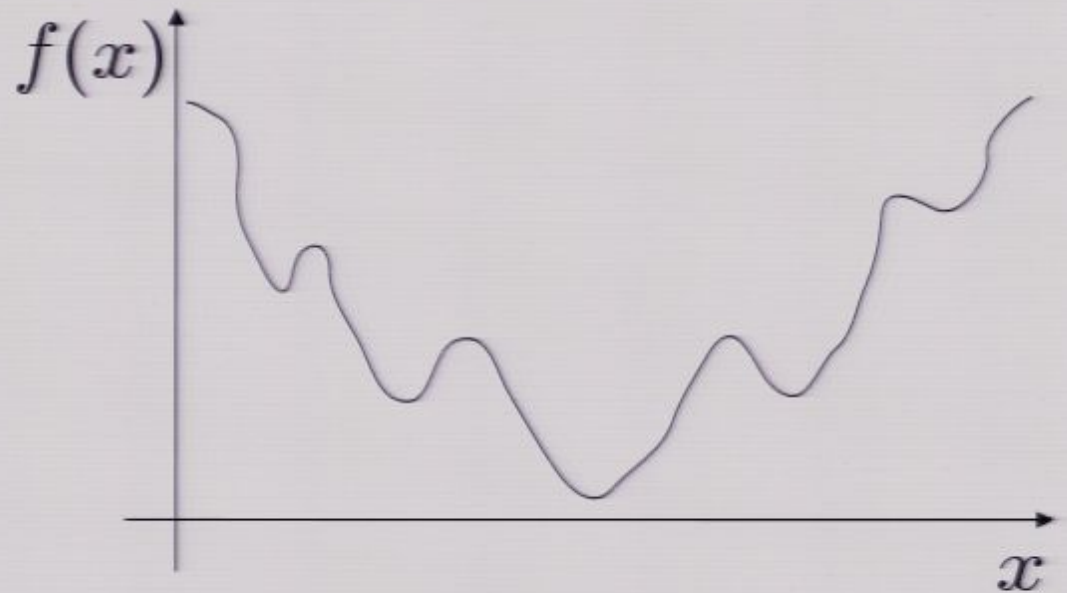
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$$T \gg \frac{1}{\Delta_{\min}^k}$$

Adiabatic quantum optimization

[Farhi *et al.* '00]

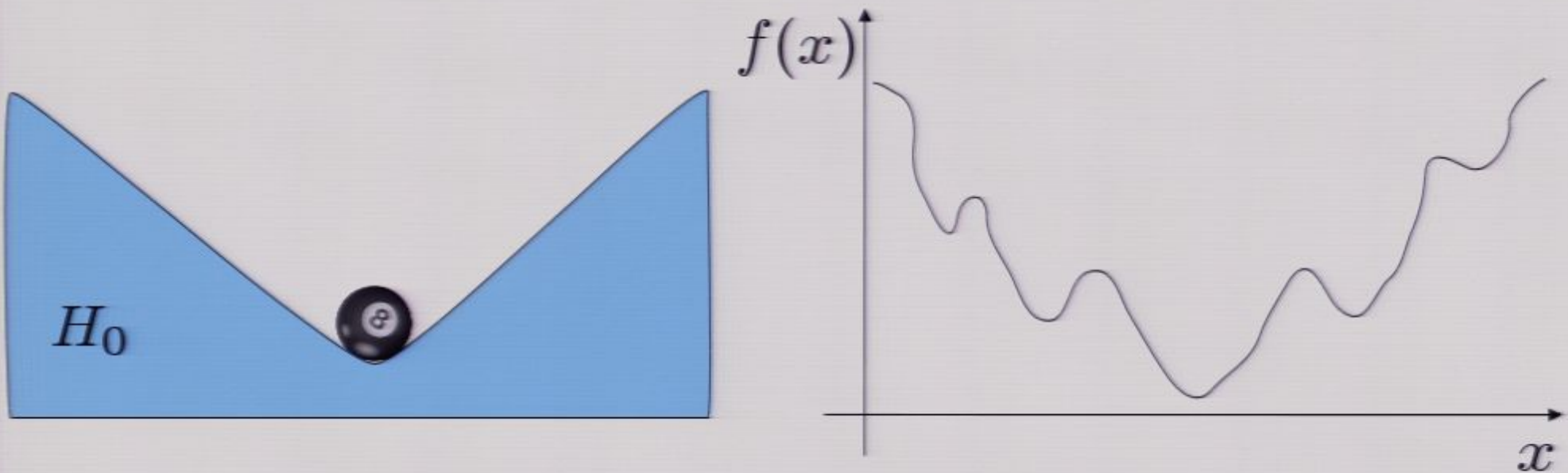
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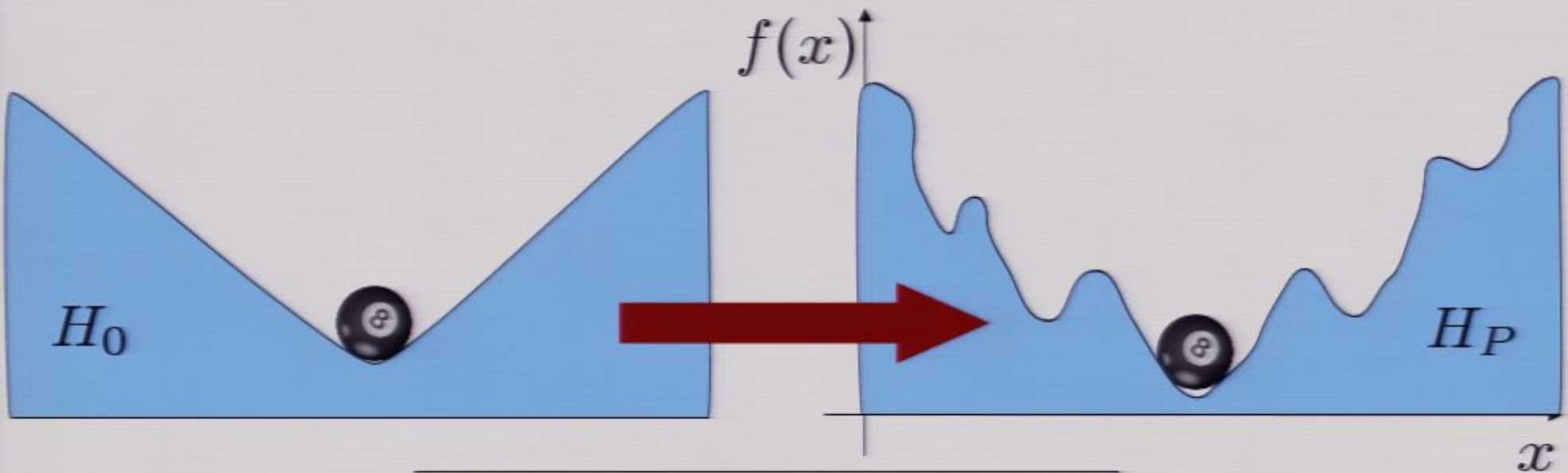
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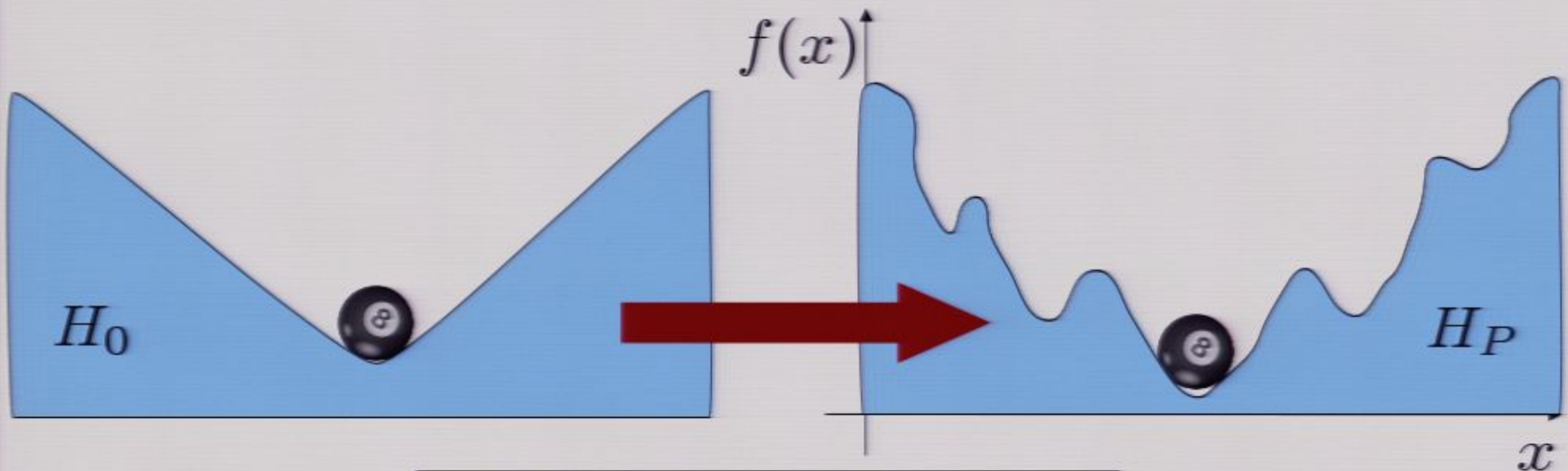
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- 3) T large enough \Rightarrow measuring reveals the minimum

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- It is quantum! Unstructured search in time $O(\sqrt{N})$ (cf Grover)



[vanDam-Mosca-Vazirani'01, Roland-Cerf'02]

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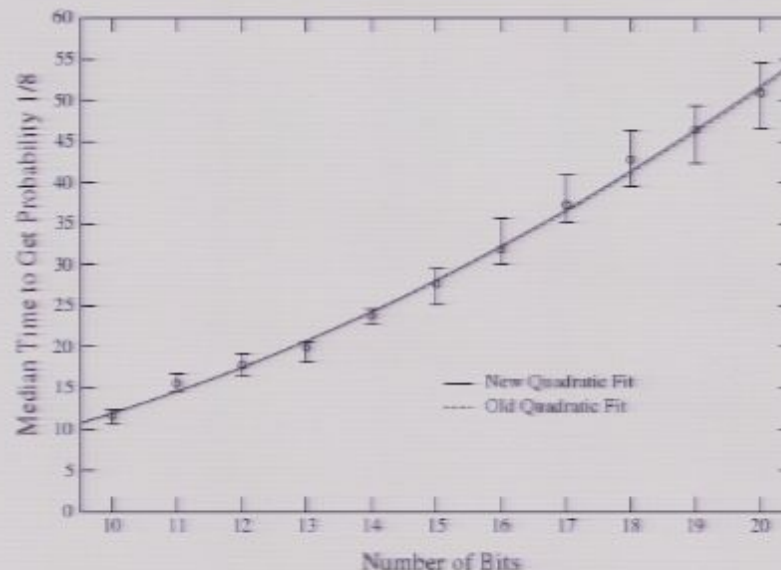
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But maybe typical gaps are only polynomial?

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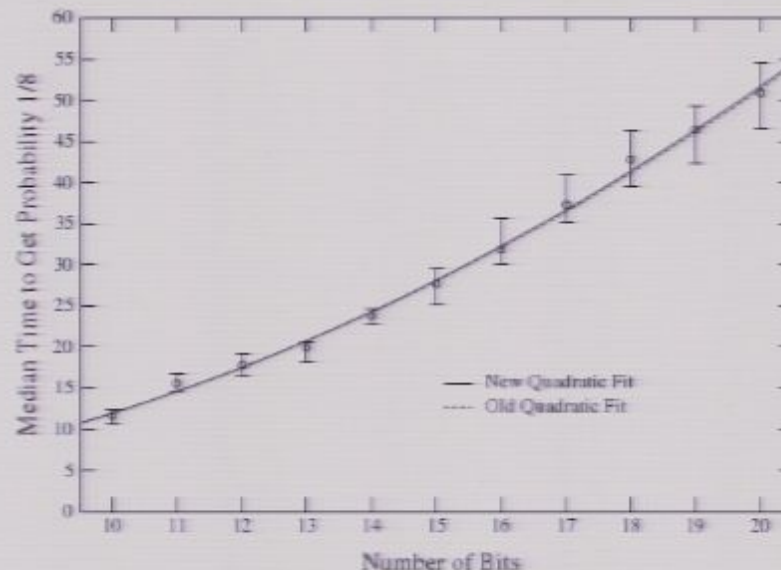
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#clauses

#clauses with bit i

#clauses with bits i, j

Random instances

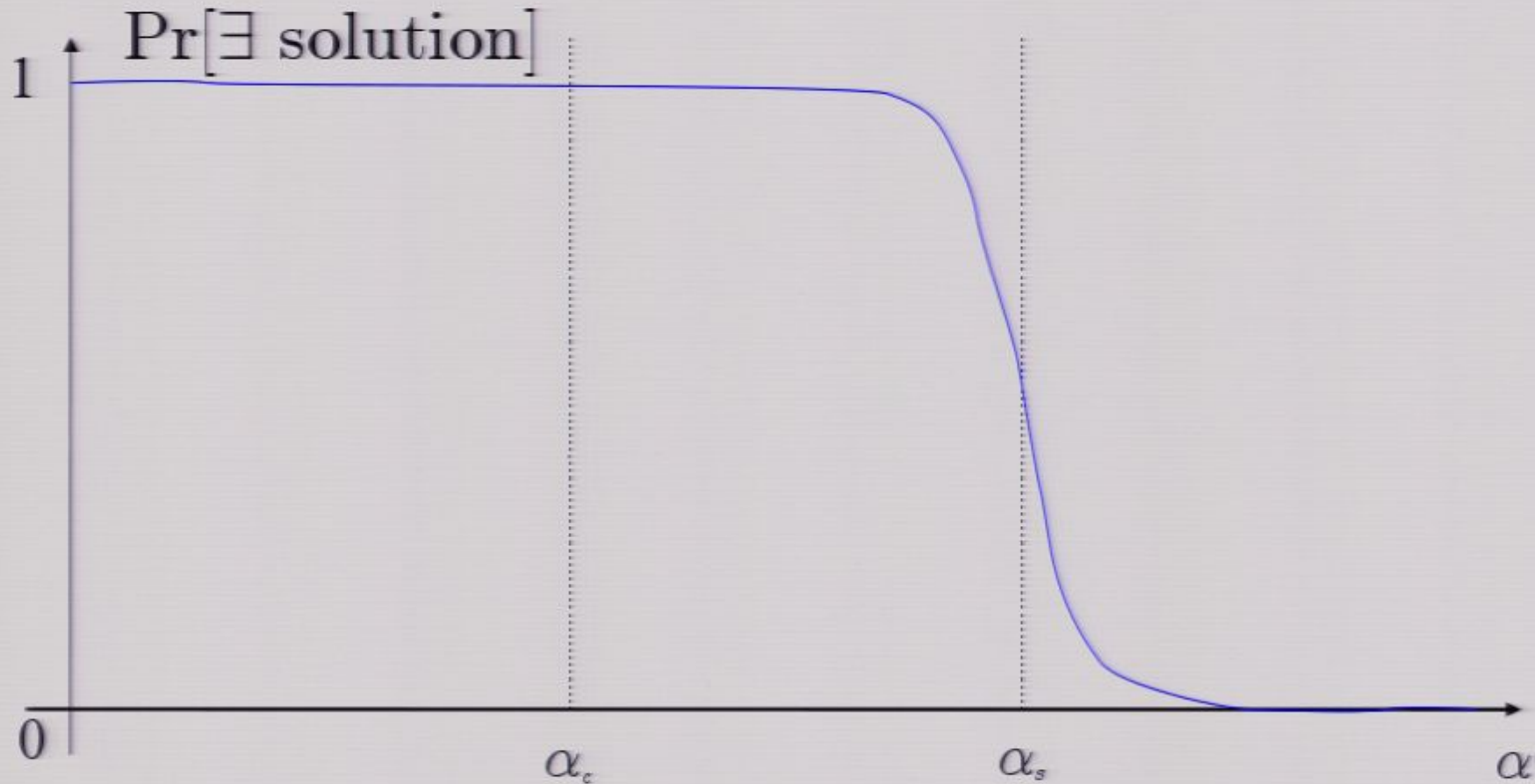
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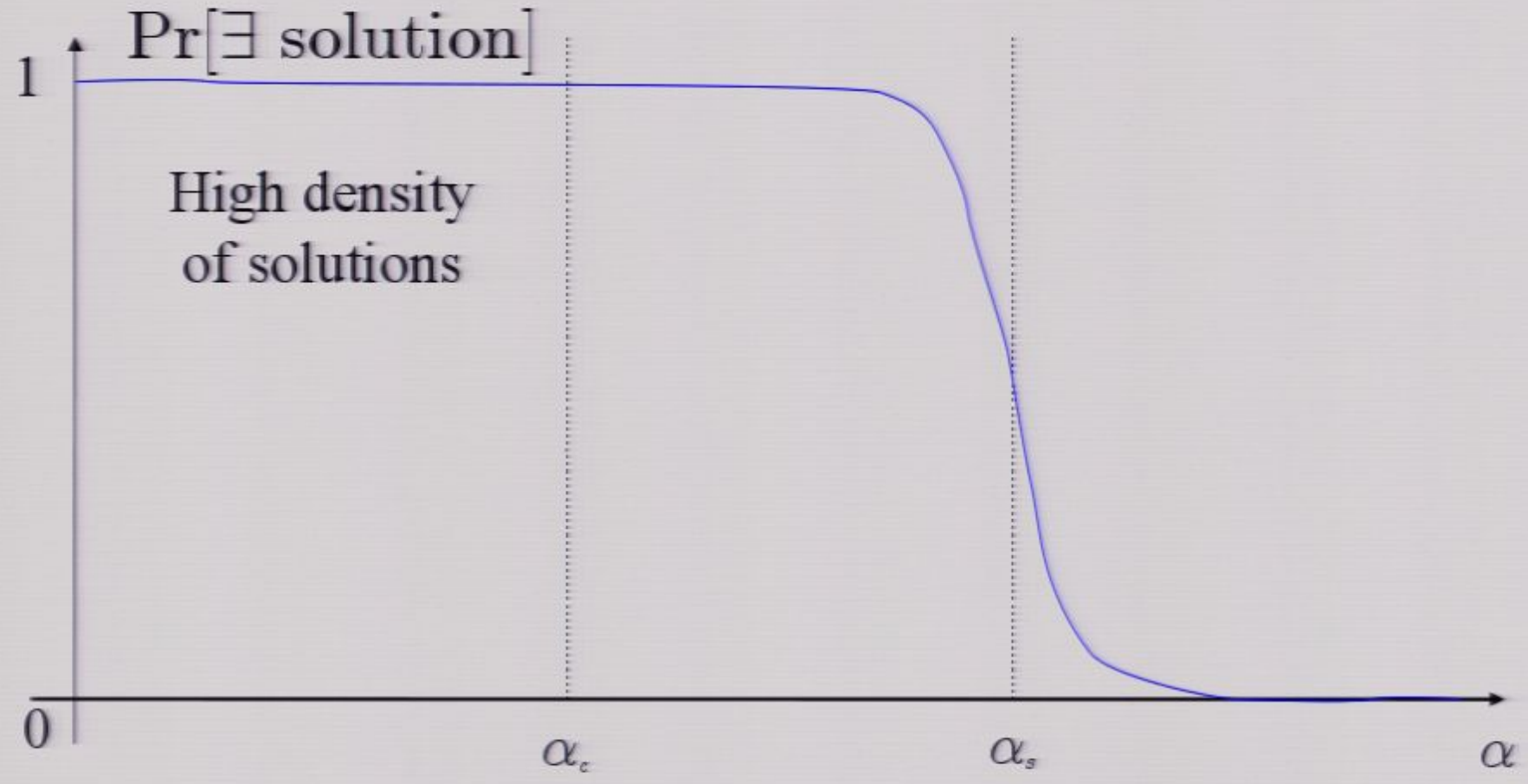
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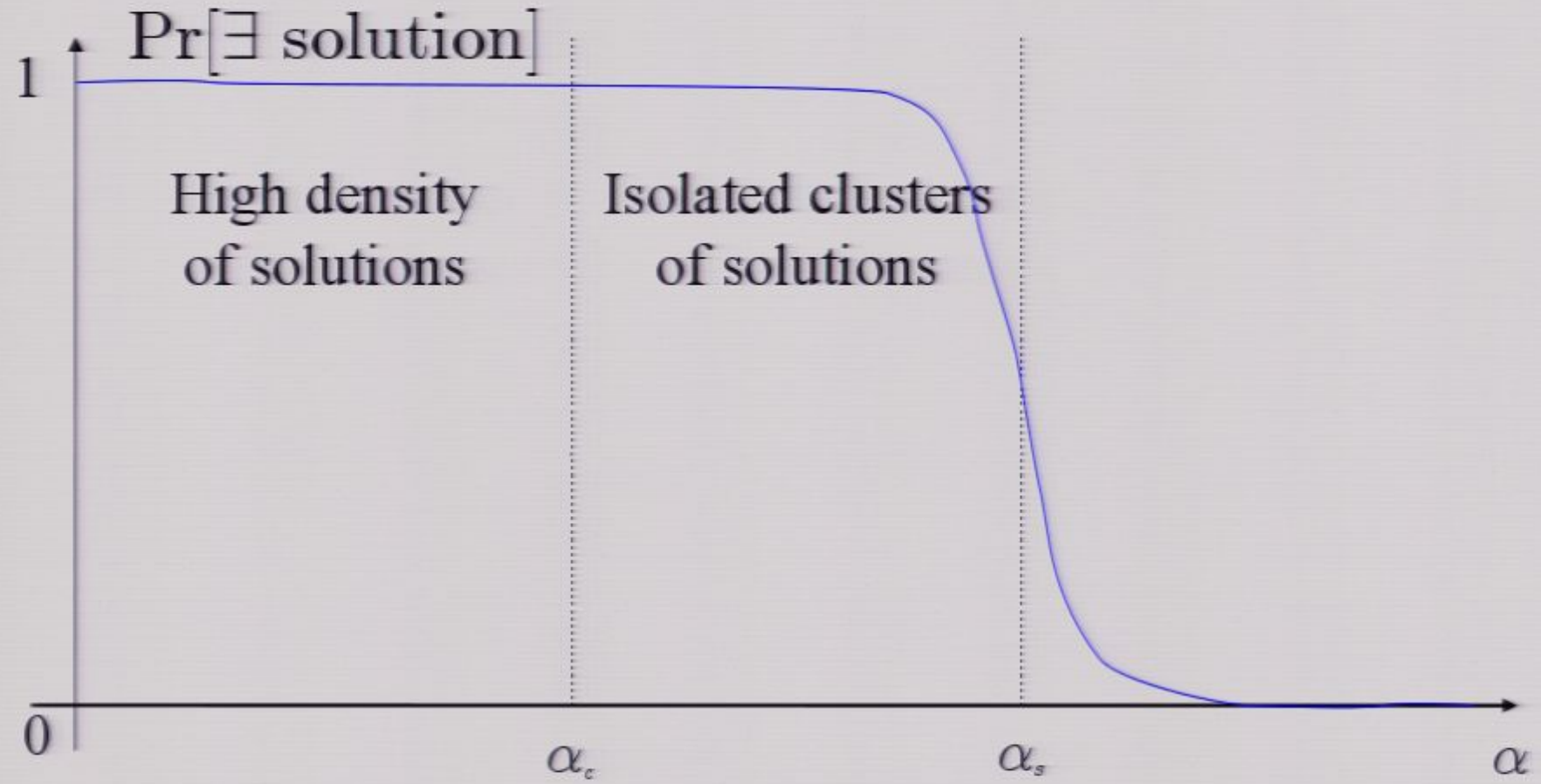
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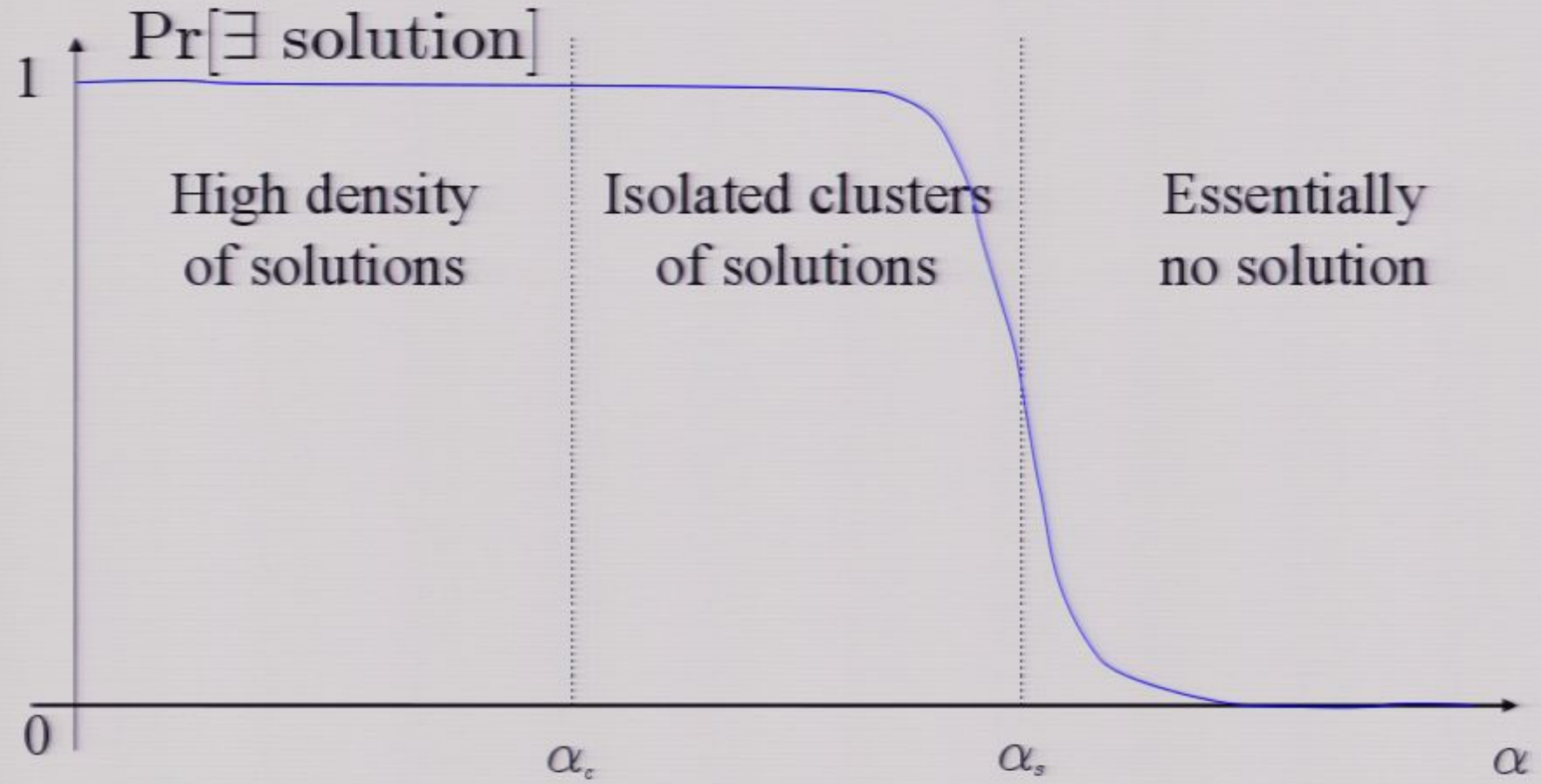
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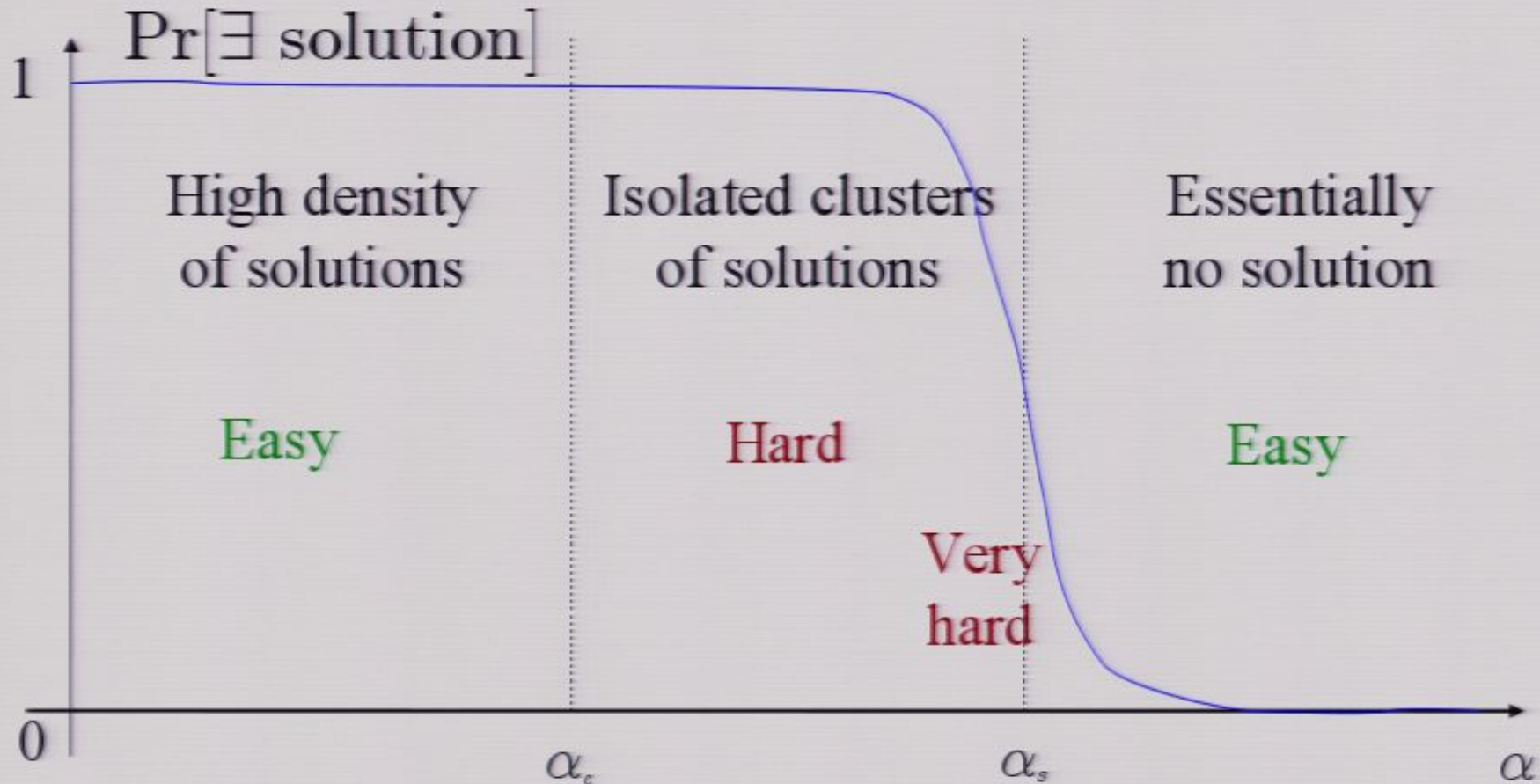
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The adiabatic algorithm

- Problem Hamiltonian $H_P = \sum_{\vec{x}} f(\vec{x}) |\vec{x}\rangle \langle \vec{x}|$

$$= M - \frac{1}{2} \sum_{i=1}^N B_i \sigma_z^{(i)} + \frac{1}{4} \sum_{i,j=1}^N J_{ij} \sigma_z^{(i)} \sigma_z^{(j)}$$

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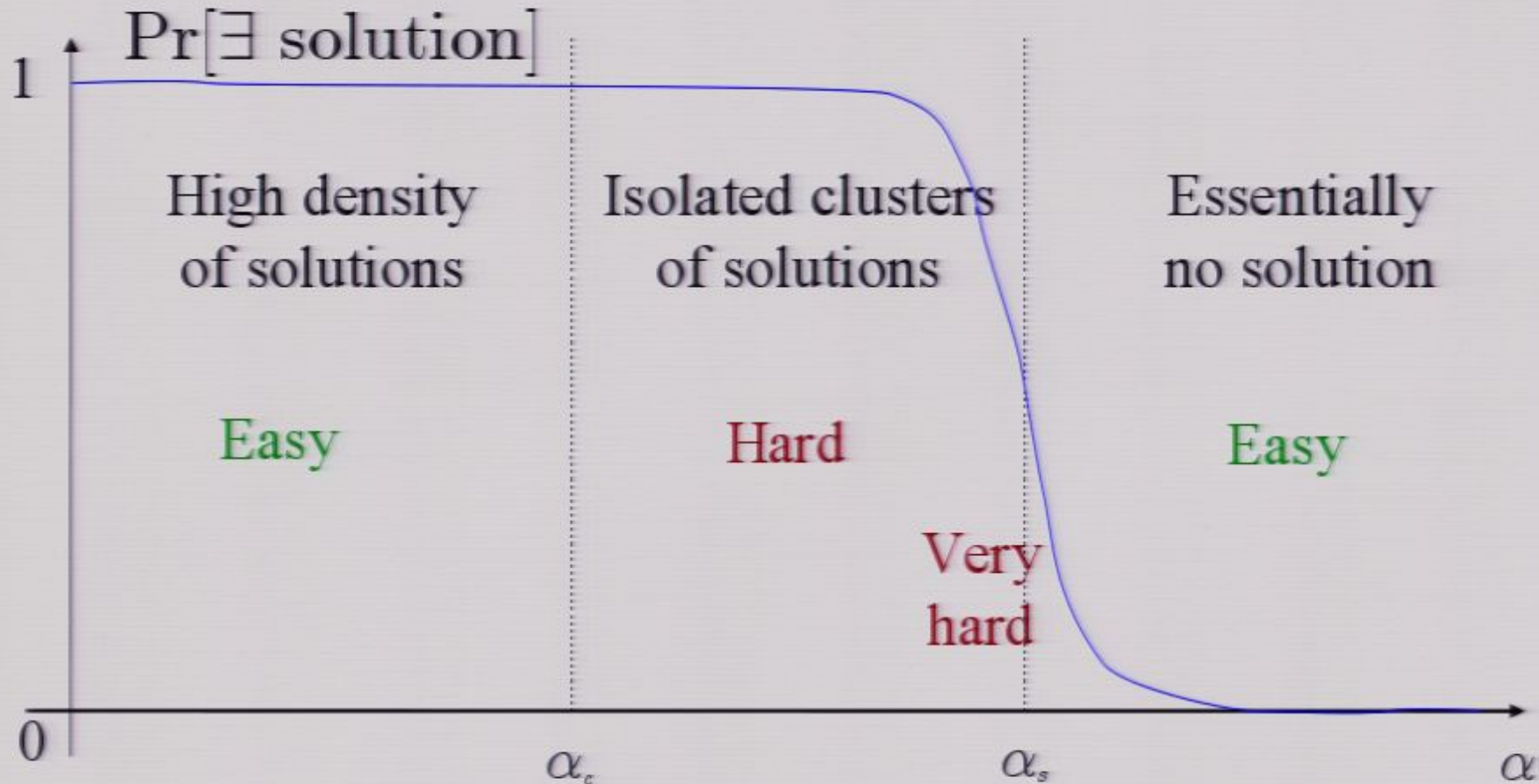
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Connection to Anderson Localization

To study the spectrum of $H(s)$ close to $s = 1$, we consider

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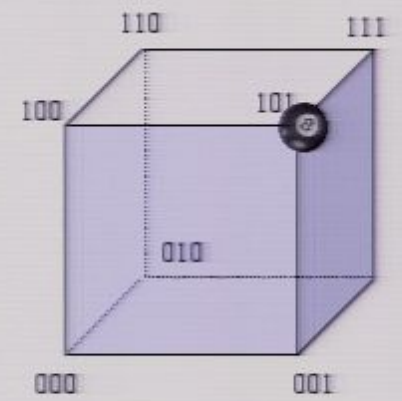
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\Rightarrow Particle hopping on a hypercube



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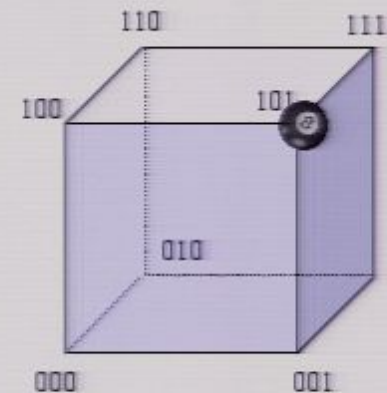
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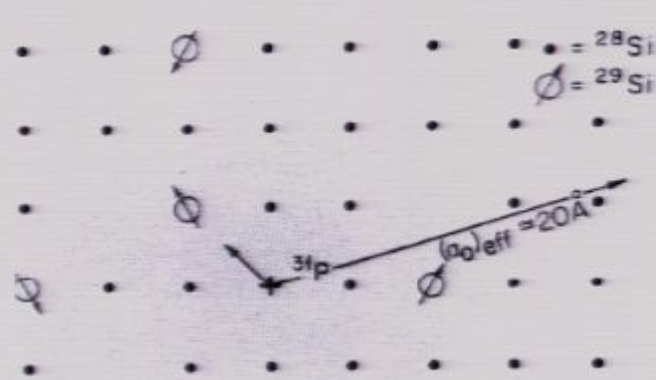
⇒ Particle hopping on a hypercube

⇒ Similar to Anderson's tight binding model



Anderson localization

“Extended states become localized due to disorder”



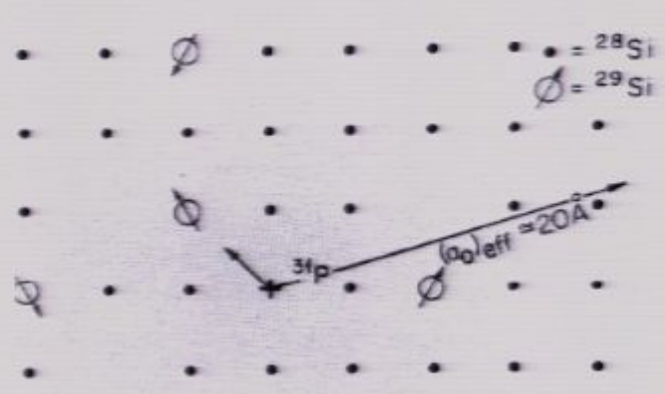
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Nobel Prize
Physics 1977

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Model:

- Grid with coupling λ
- Random energies



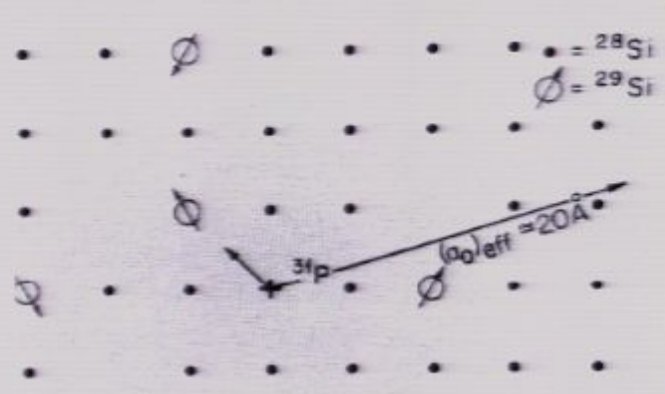
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$\lambda > \lambda_c \rightarrow$ Extended state \rightarrow Metal

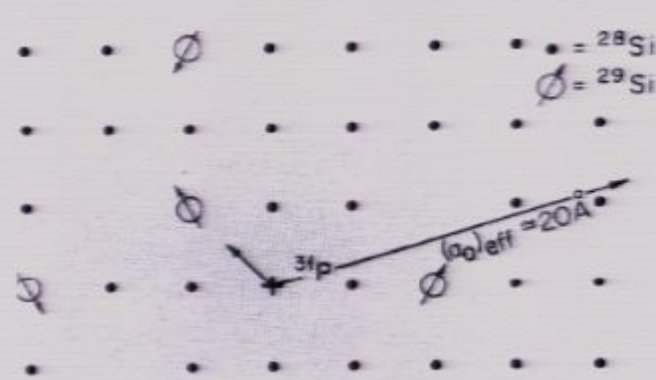
$\lambda < \lambda_c \rightarrow$ Localized state \rightarrow Insulator

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- Grid with coupling λ
- Random energies



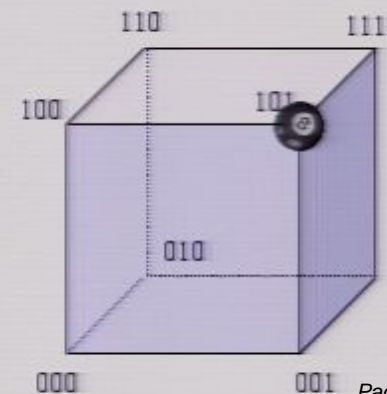
P. Anderson
Nobel Prize
Physics 1977

$\lambda > \lambda_c \rightarrow$ Extended state \rightarrow Metal

$\lambda < \lambda_c \rightarrow$ Localized state \rightarrow Insulator

In our case:

- Hypercube with coupling λ
- Energies from random Exact-Cover 3

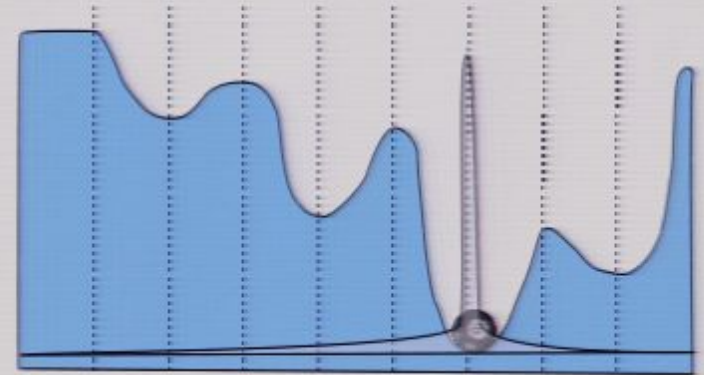


Localized and extended states

Localized and extended states

$$\lambda = 0$$

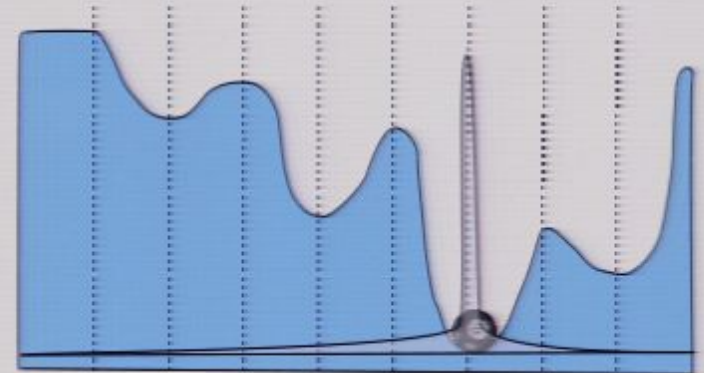
- State is localized



Localized and extended states

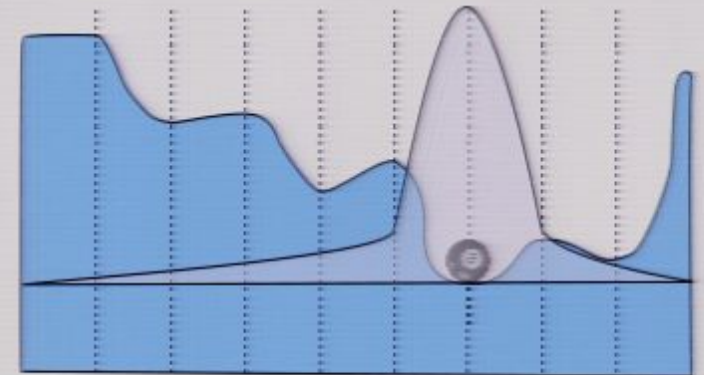
$$\lambda = 0$$

- State is localized



$$\lambda > 0$$

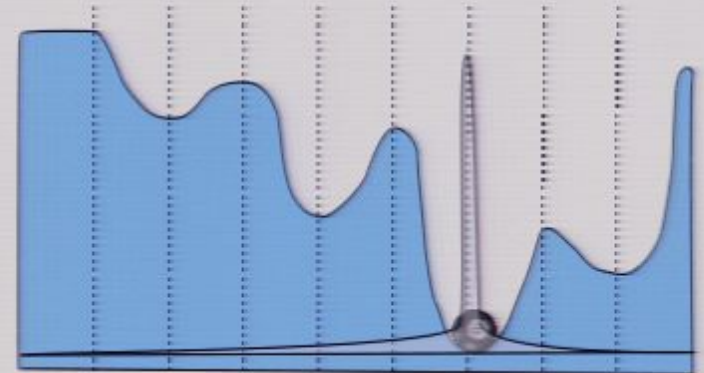
- Transverse field “spreads” the state



Localized and extended states

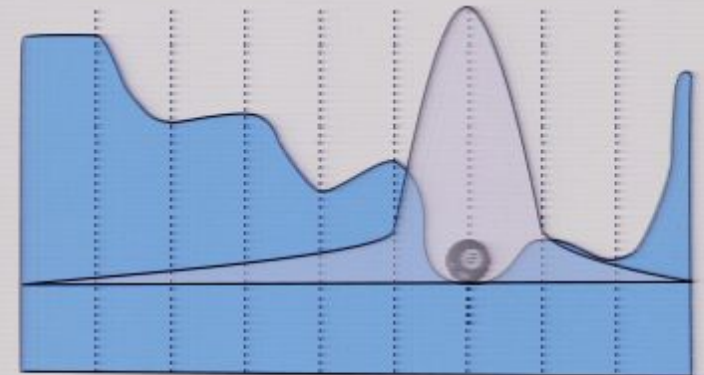
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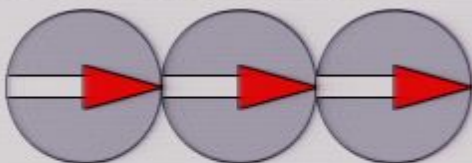
$$\lambda > 0$$

- Transverse field “spreads” the state



$$\lambda \gg 1$$

- State is extended



Localized and extended states

$\lambda = 0$

- State is localized



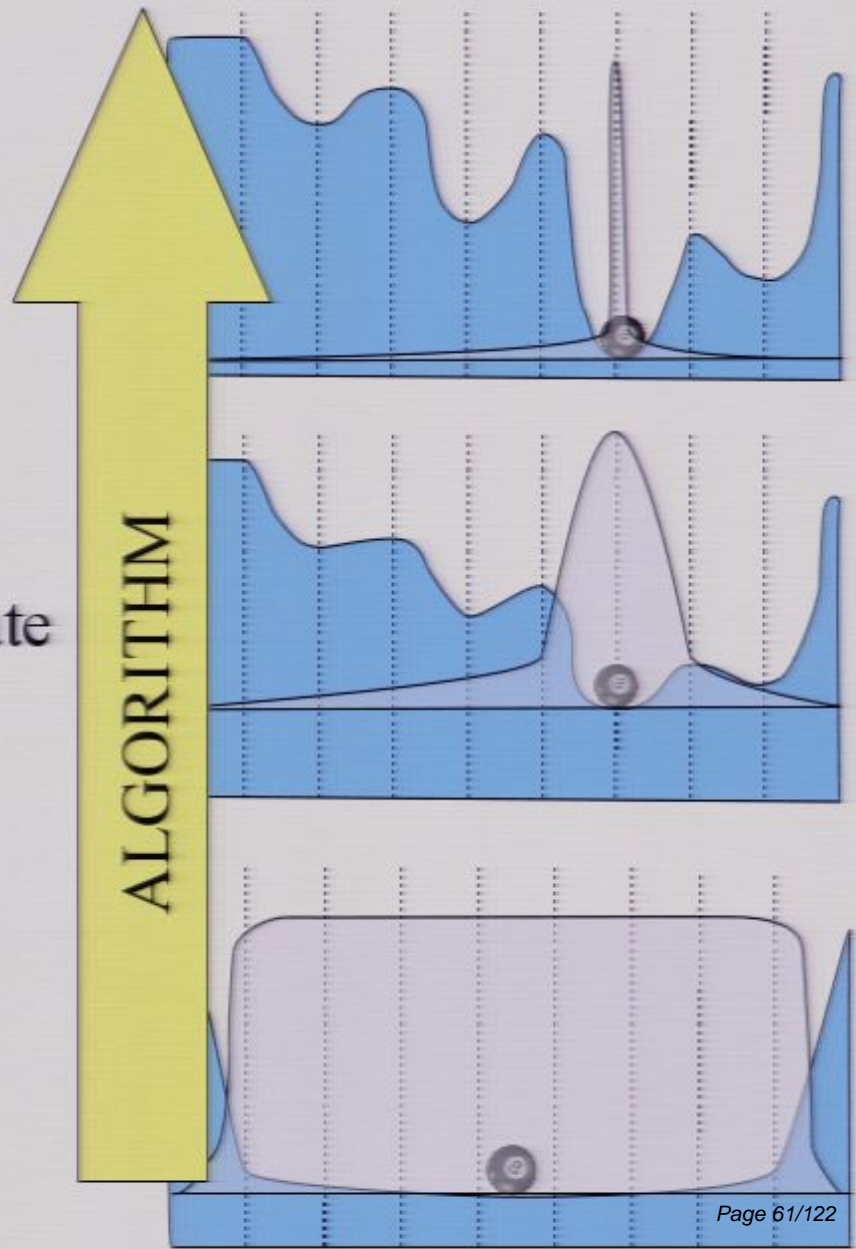
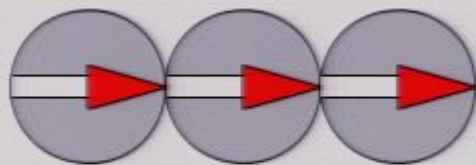
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Localized and extended states

$\lambda = 0$

- State is localized



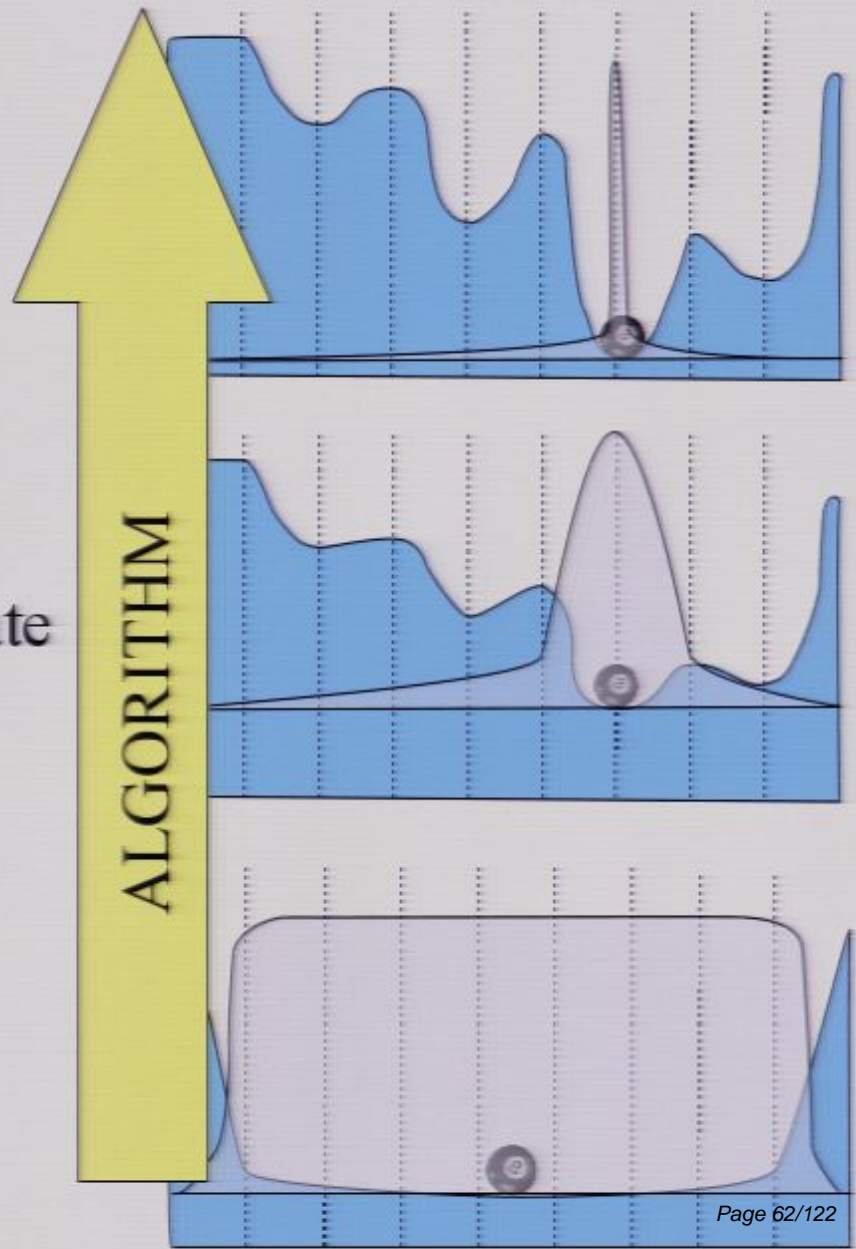
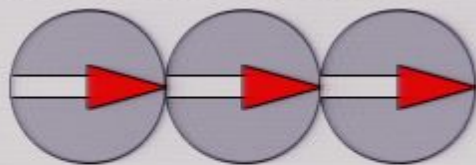
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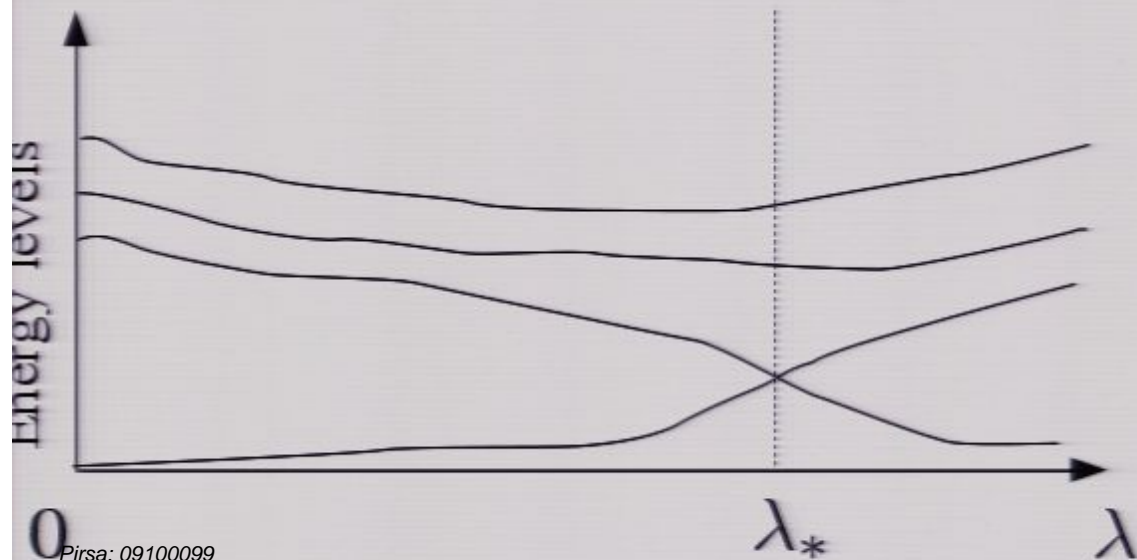
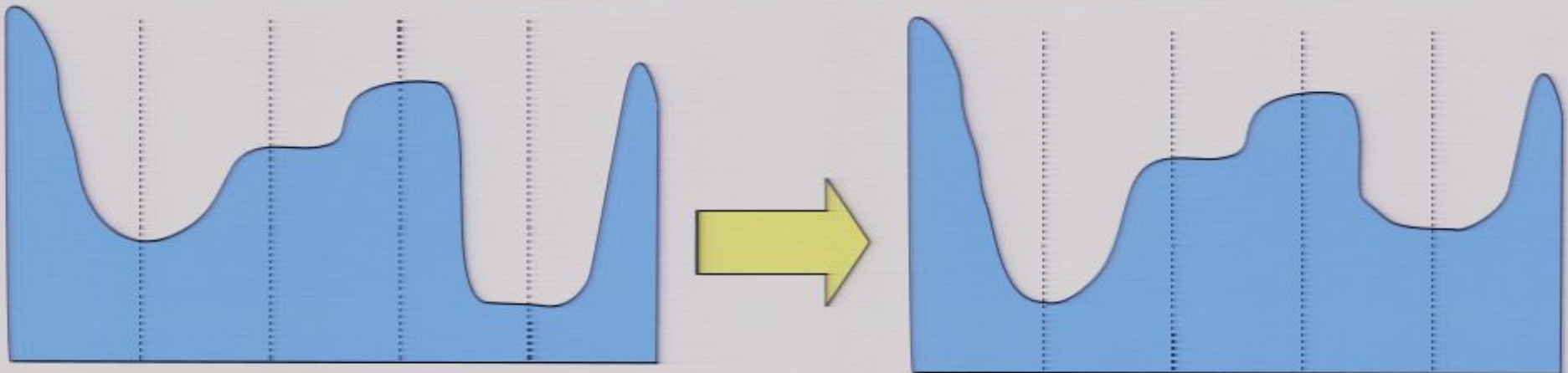


Tunneling: extended state

What if a local minimum later becomes the global minimum?

$$\lambda > \lambda_*$$

$$\lambda < \lambda_*$$

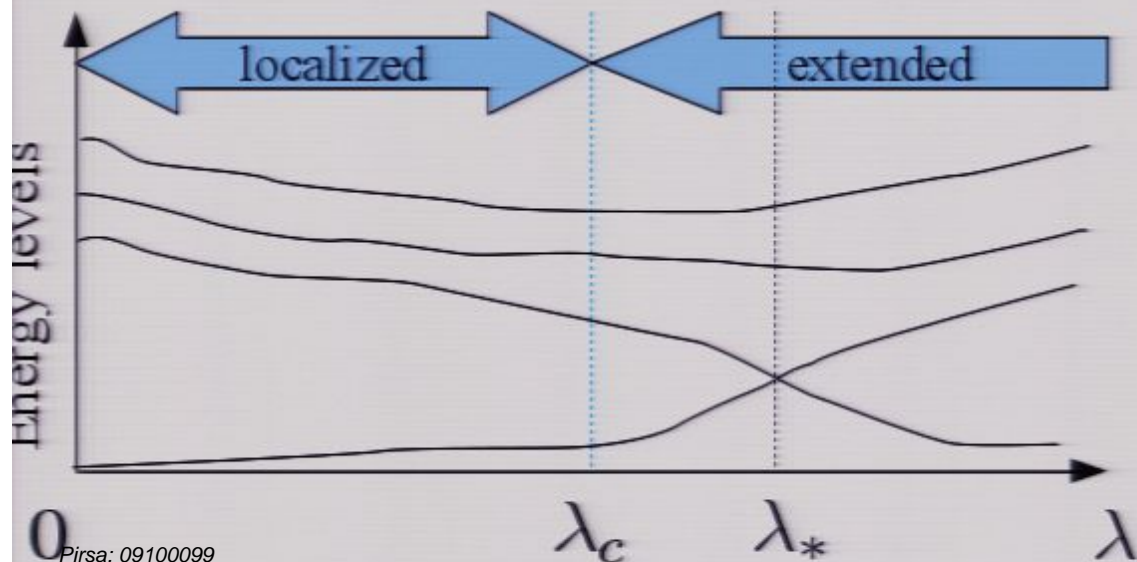
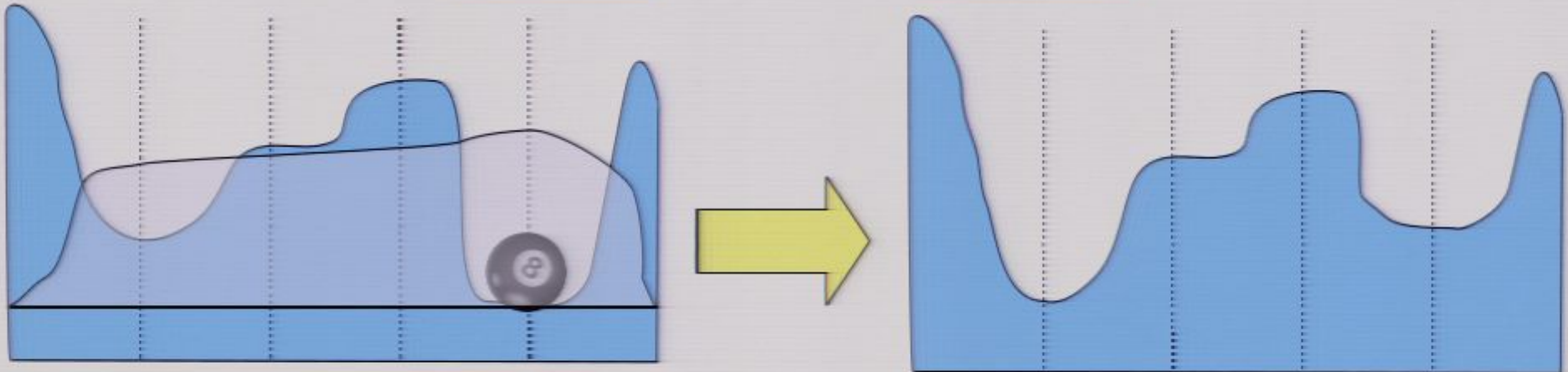


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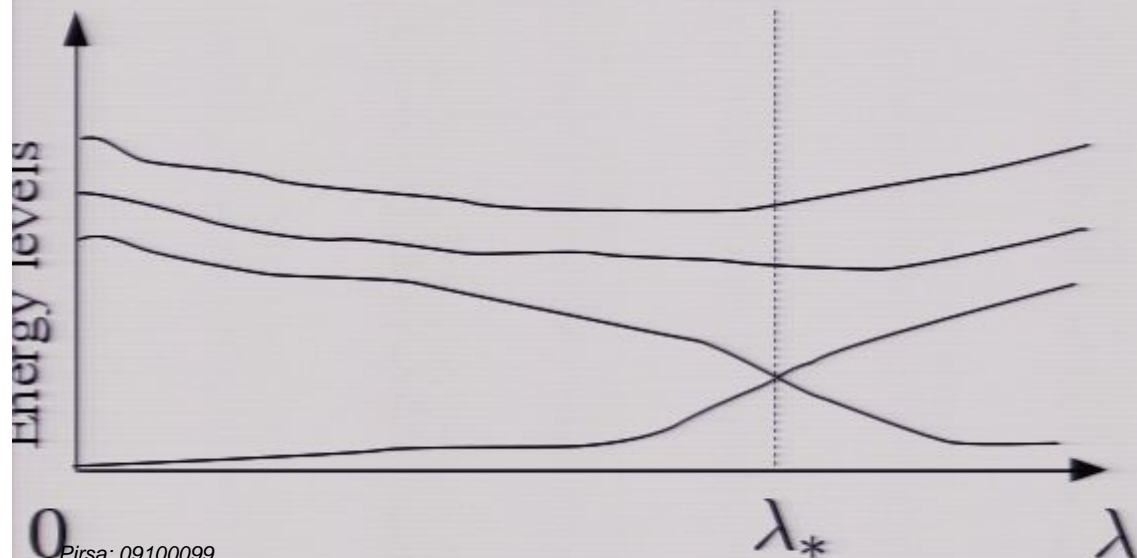
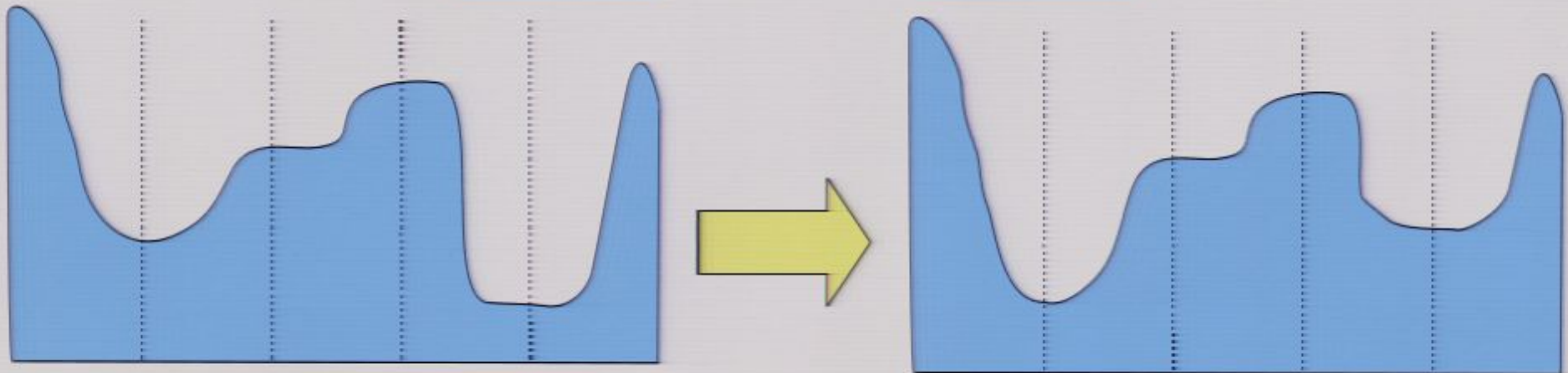


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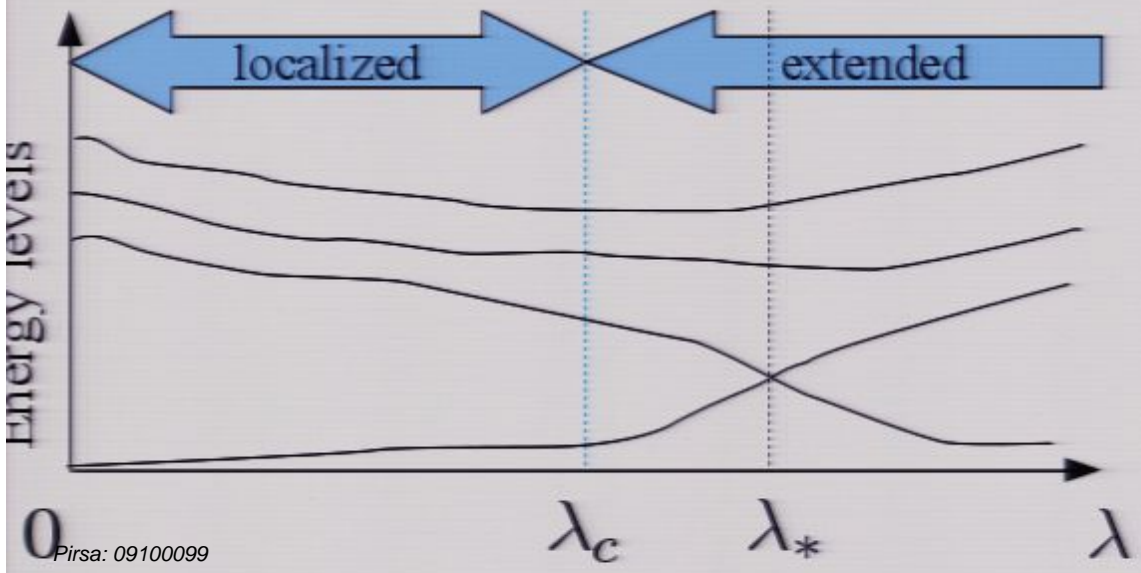
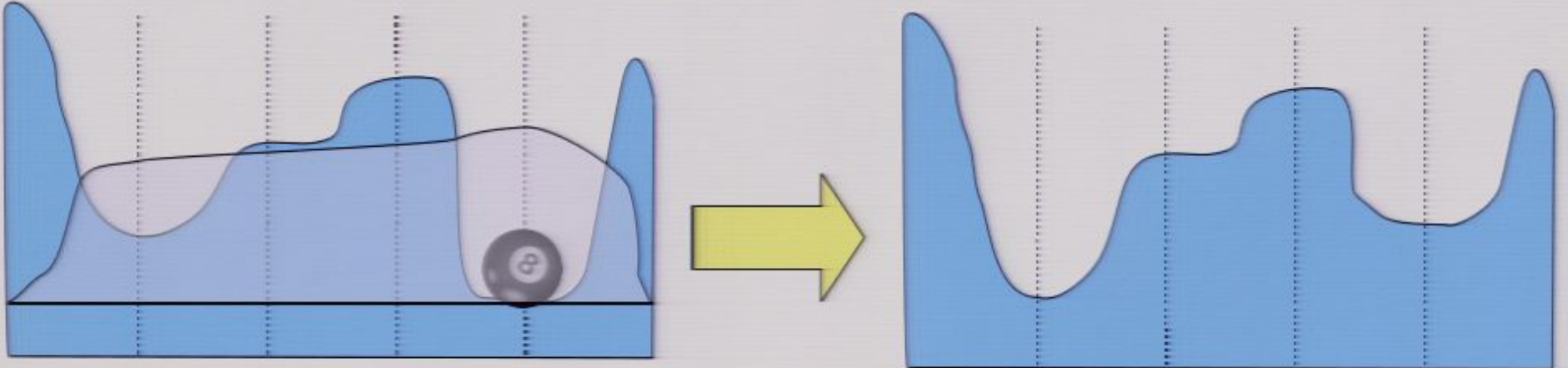


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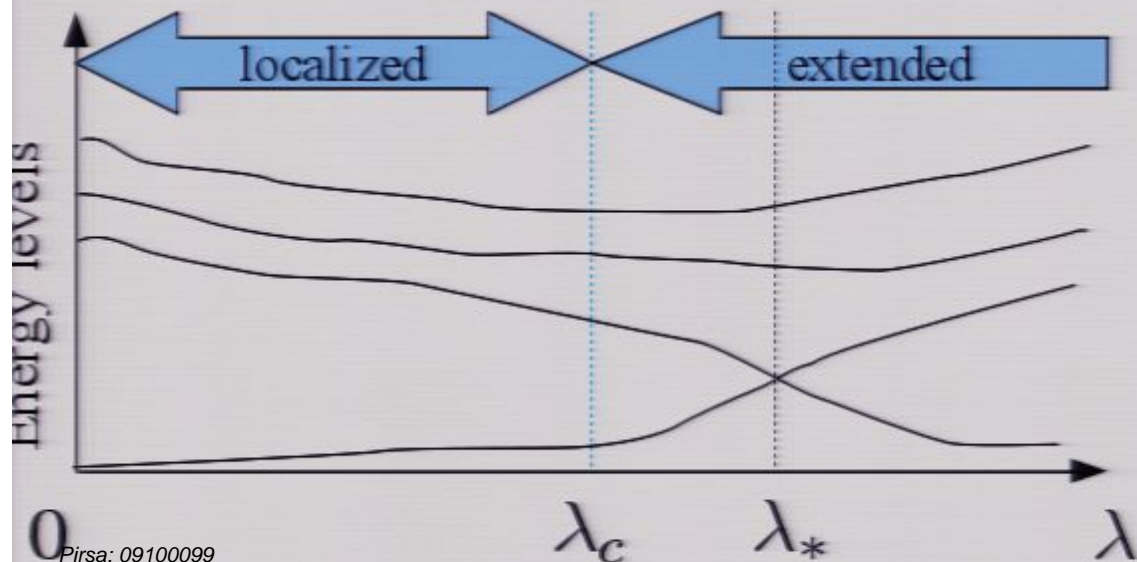
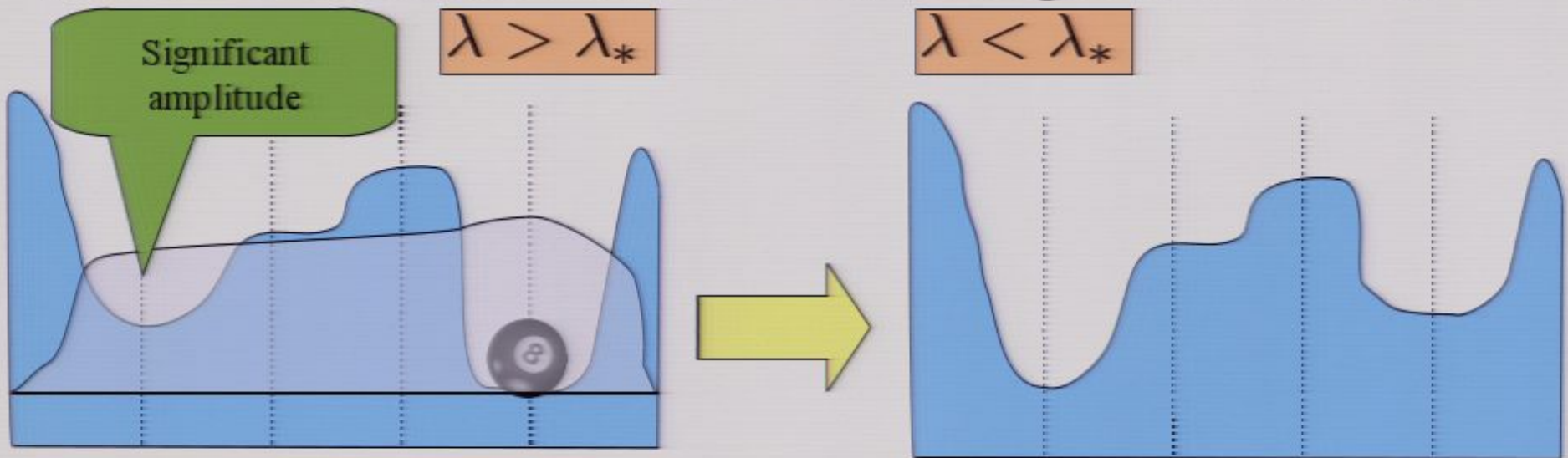
$\lambda > \lambda_*$

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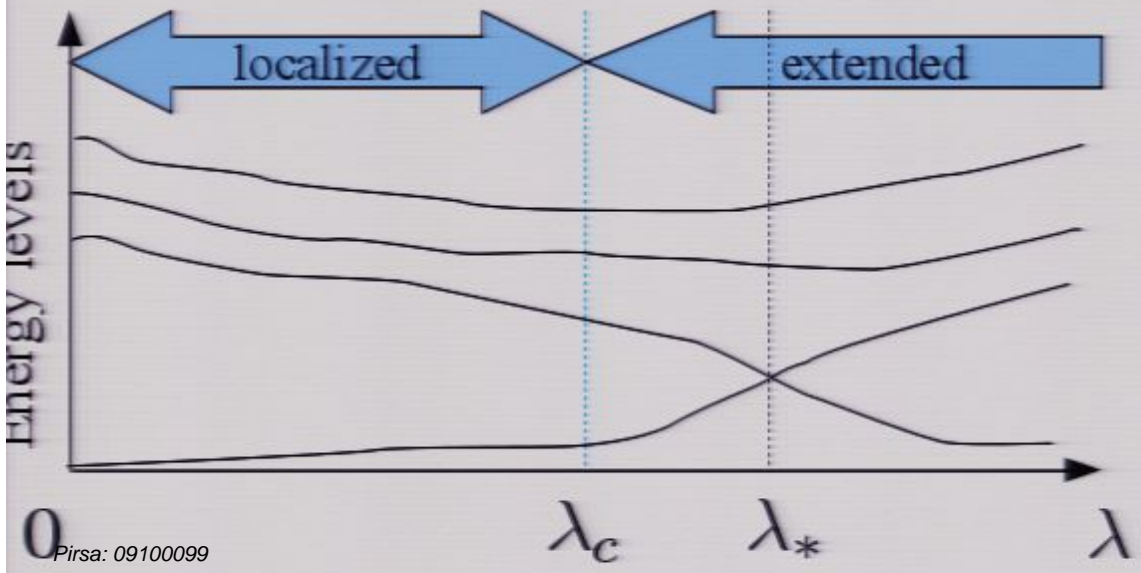
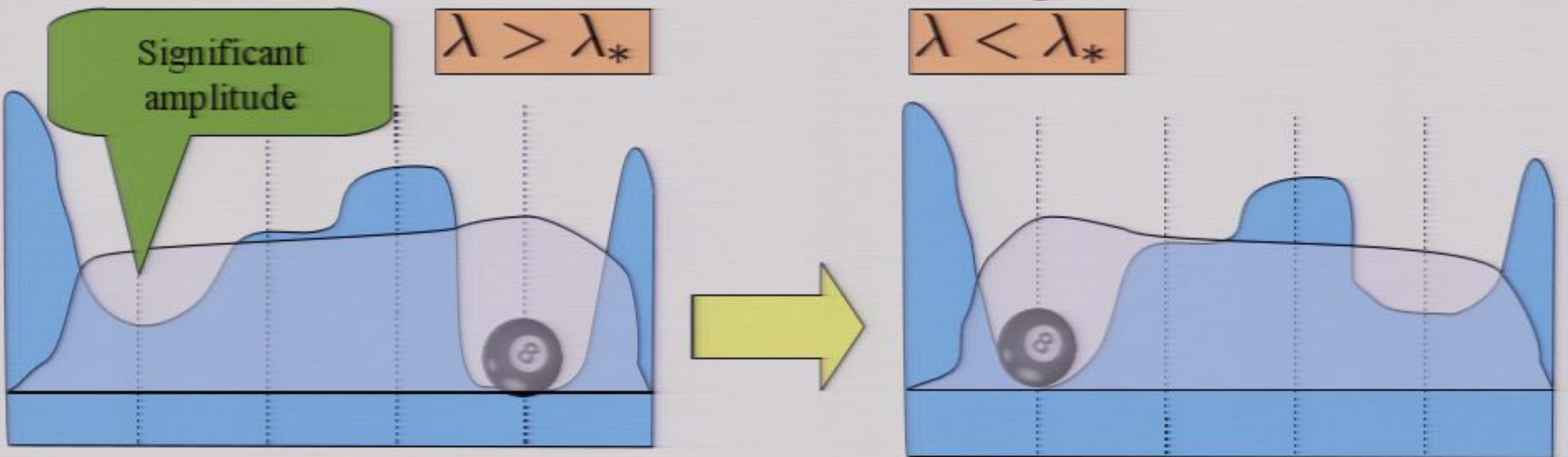
Tunneling: extended state

What if a local minimum later becomes the global minimum?



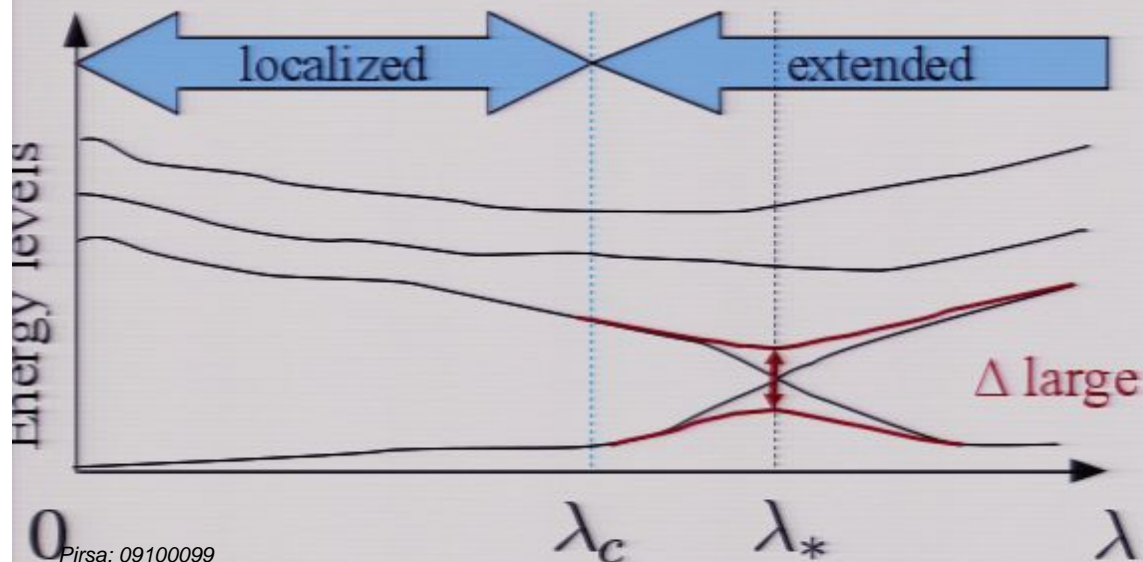
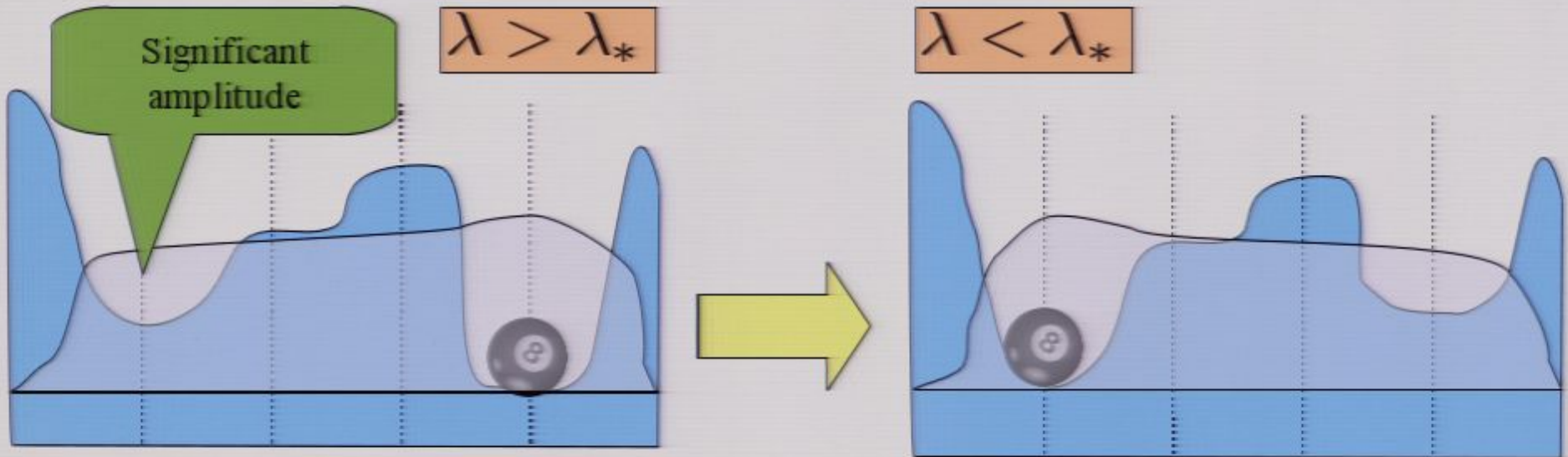
Tunneling: extended state

What if a local minimum later becomes the global minimum?



Tunneling: extended state

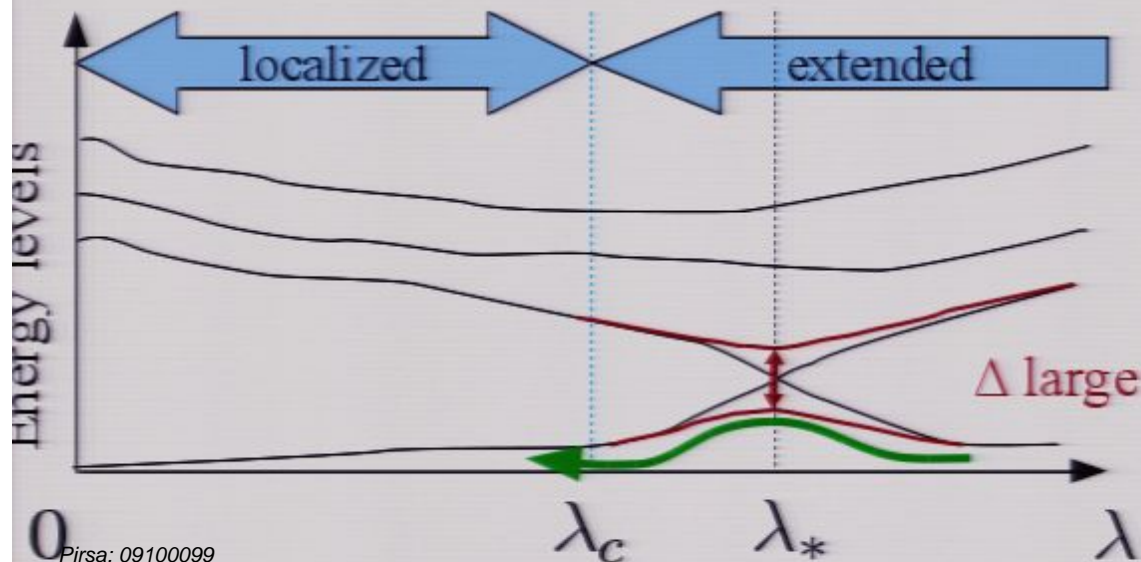
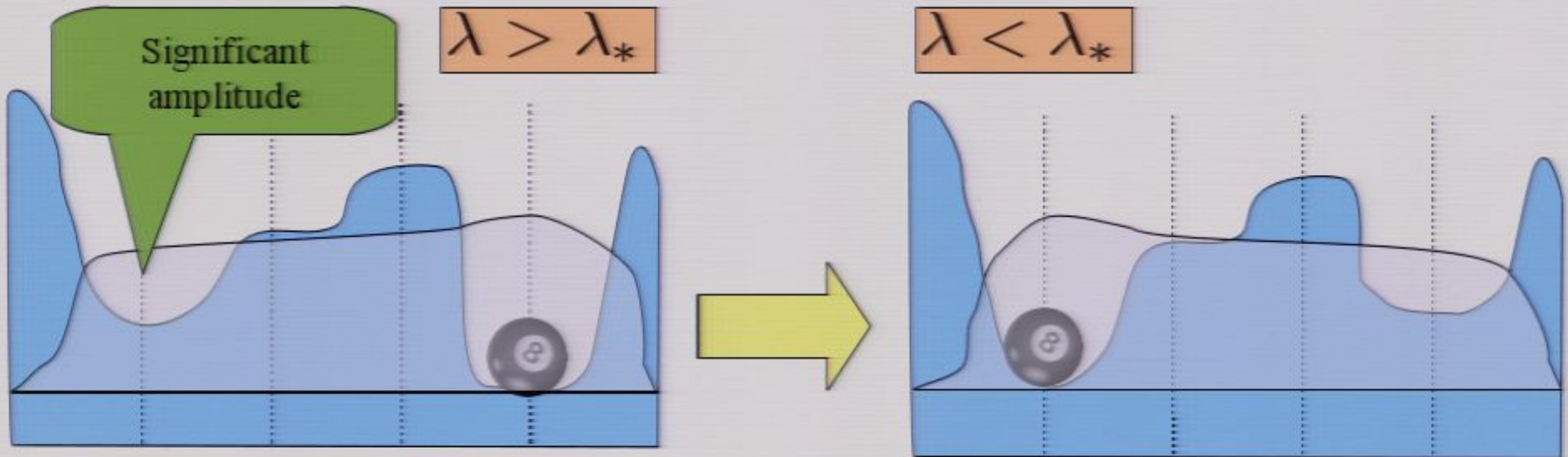
What if a local minimum later becomes the global minimum?



Large anti-crossing gap

Tunneling: extended state

What if a local minimum later becomes the global minimum?



Large anti-crossing gap

→ Tunneling

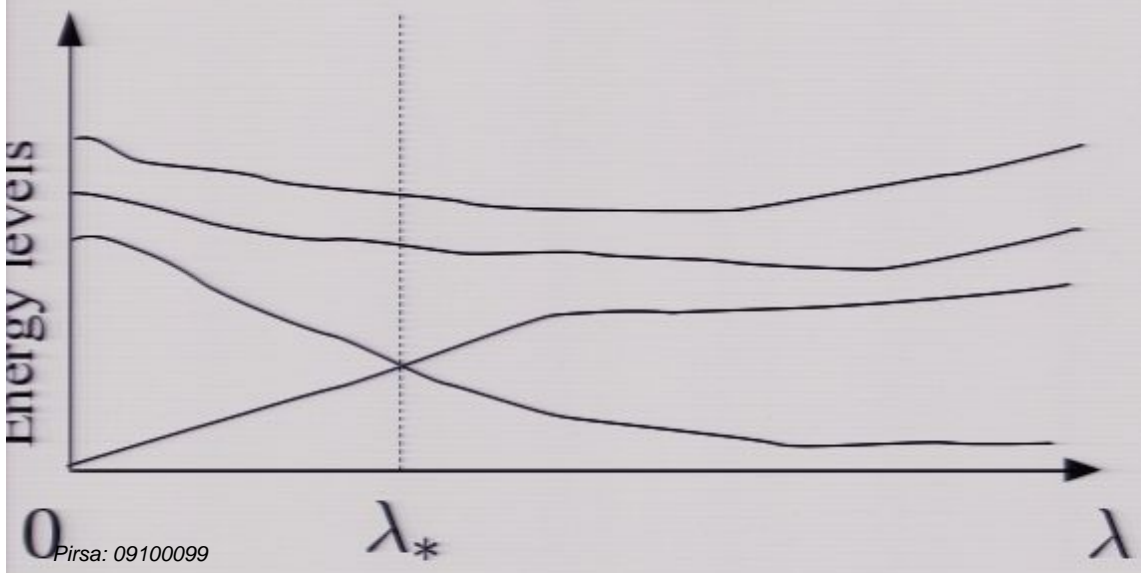
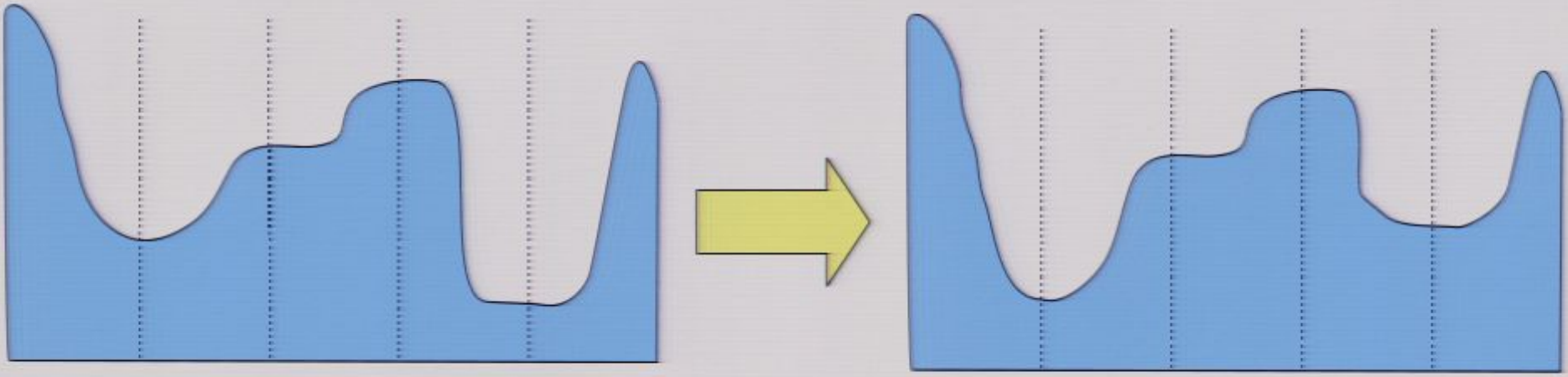


Tunneling: localized state

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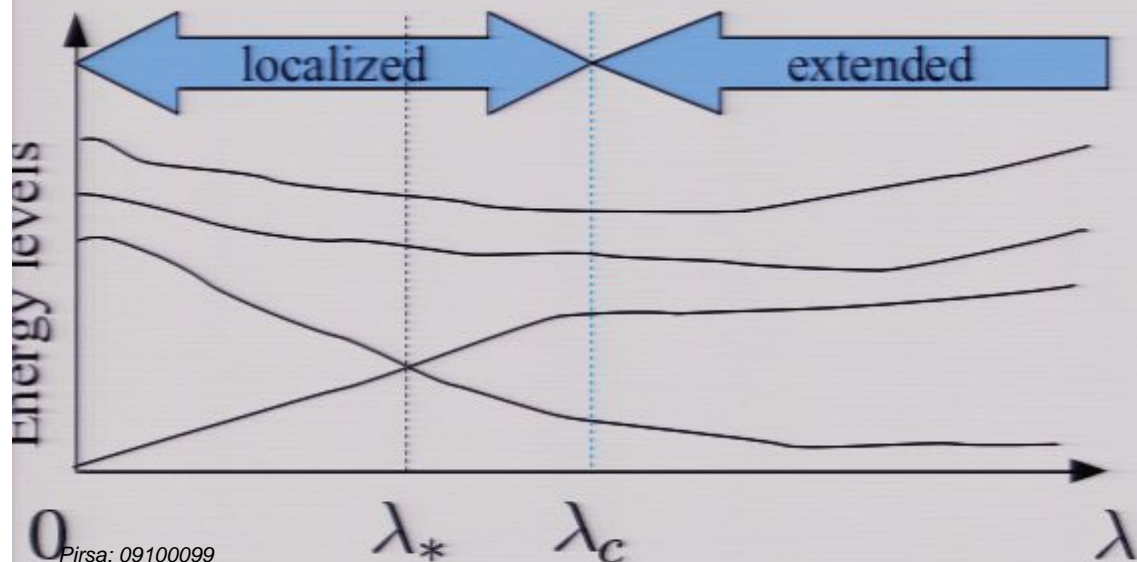
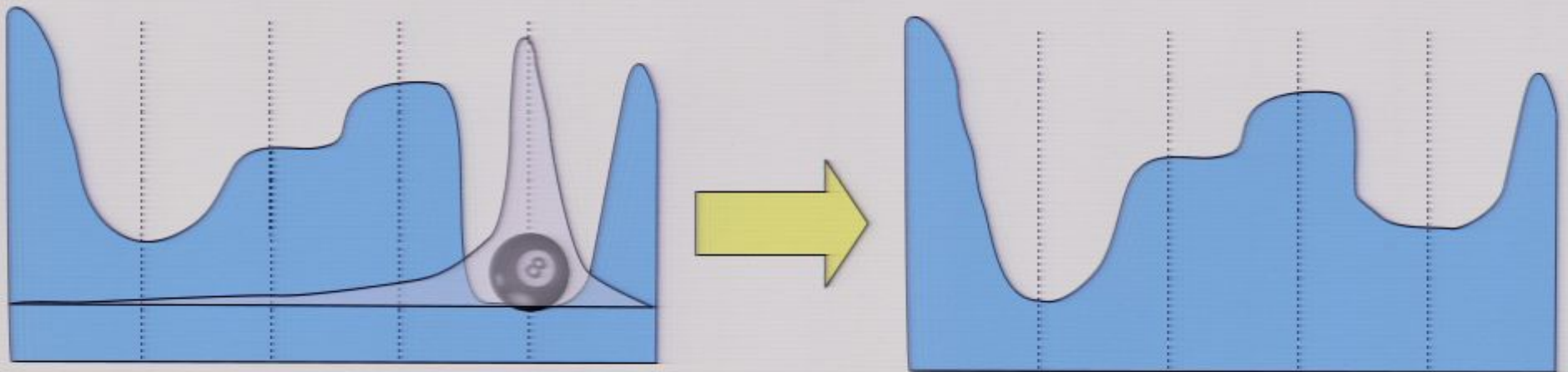


Tunneling: localized state

What if a local minimum later becomes the global minimum?

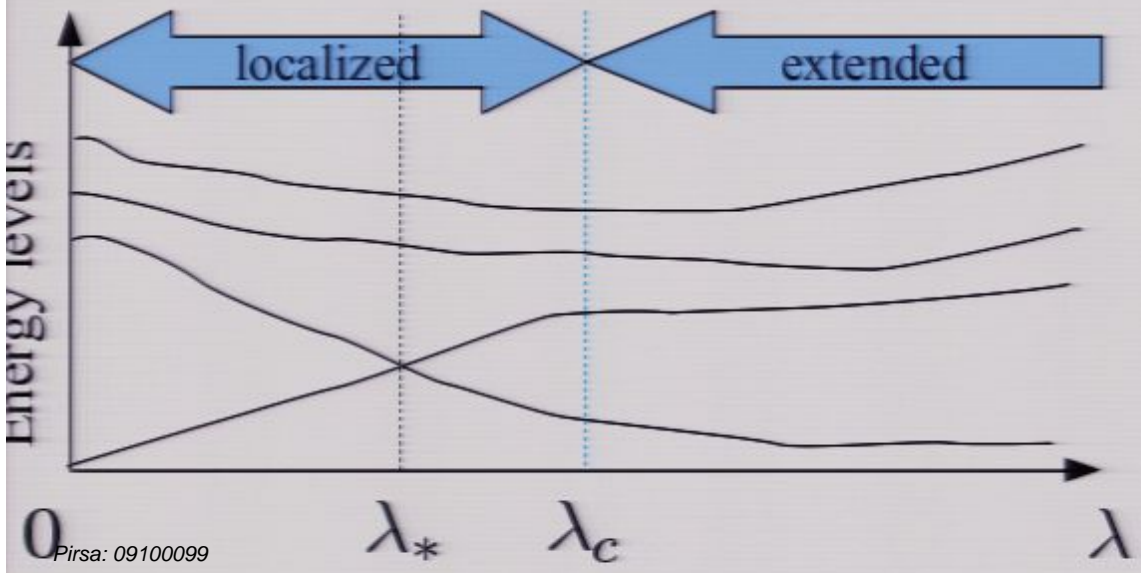
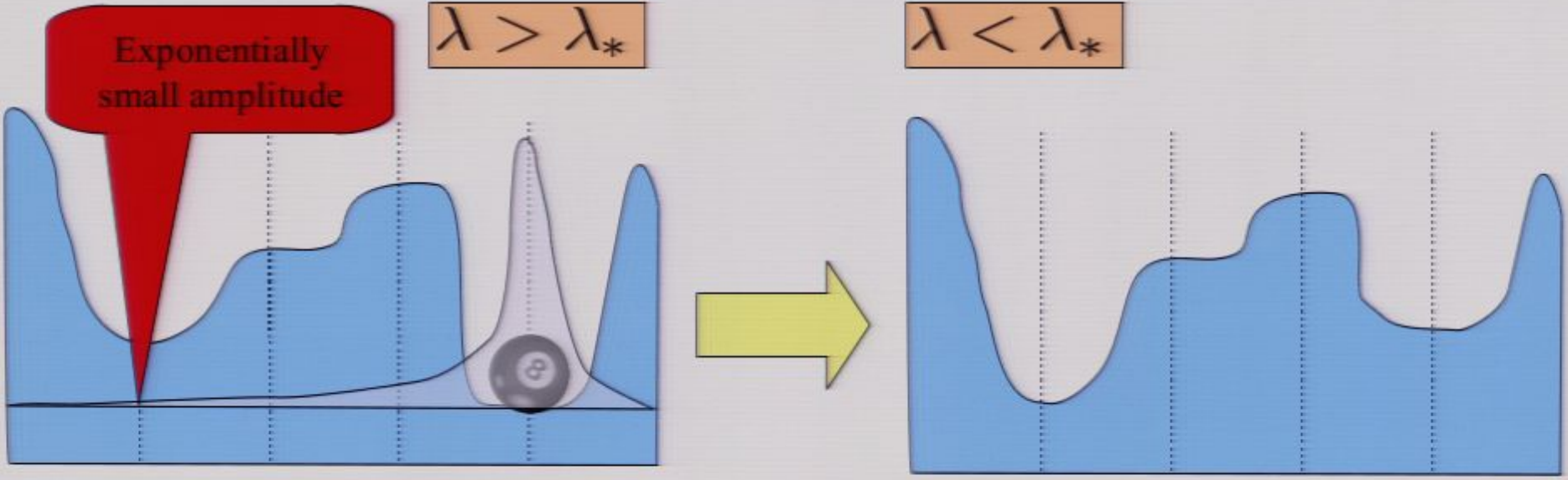
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$$\lambda < \lambda_*$$



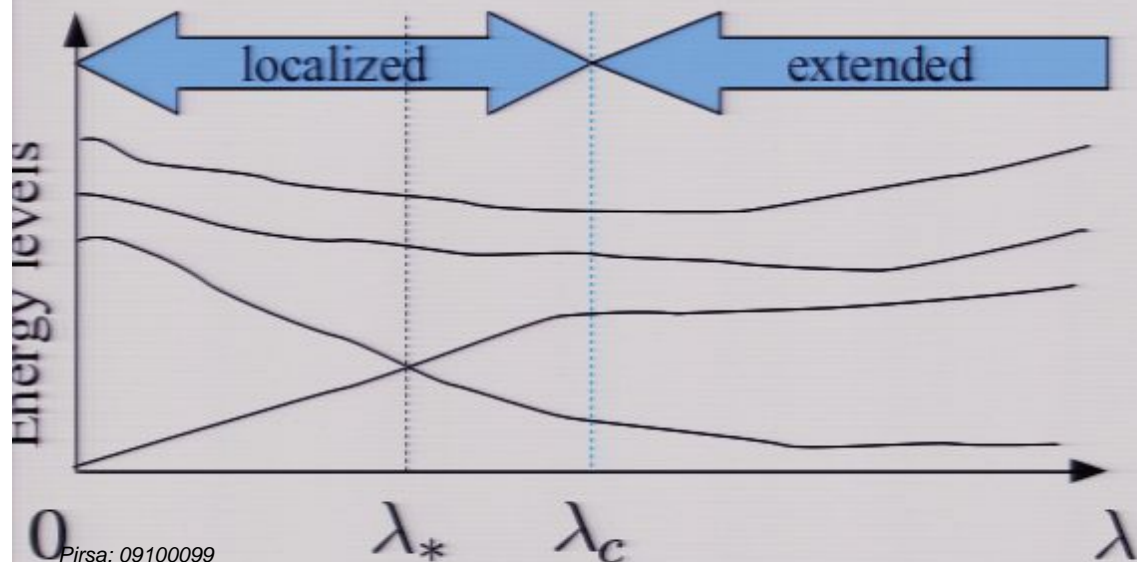
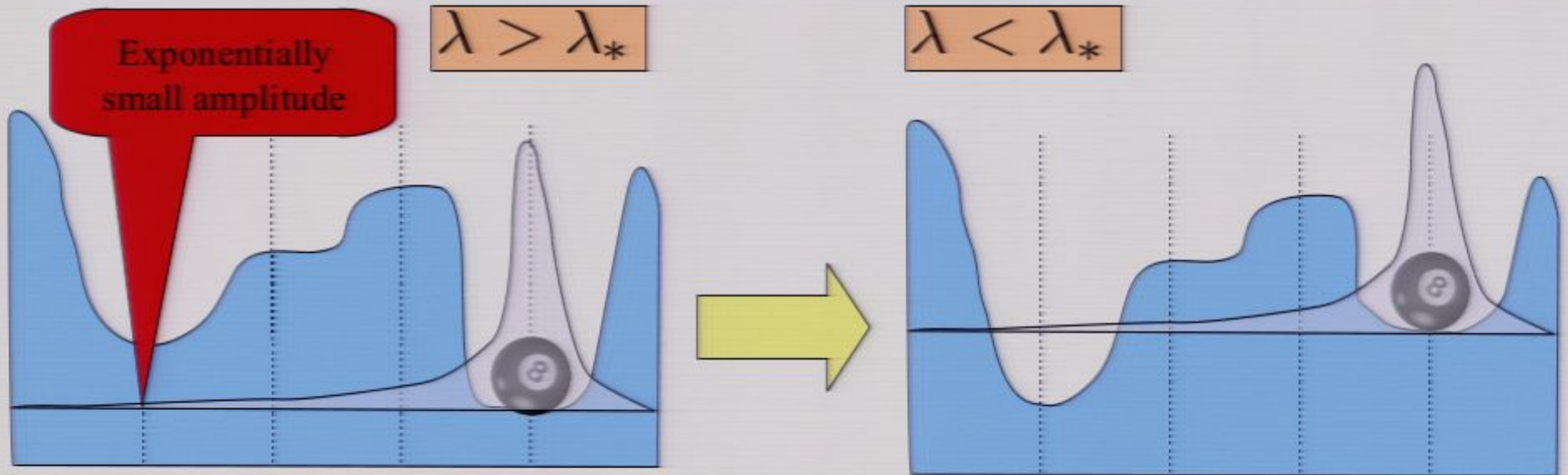
Tunneling: localized state

What if a local minimum later becomes the global minimum?



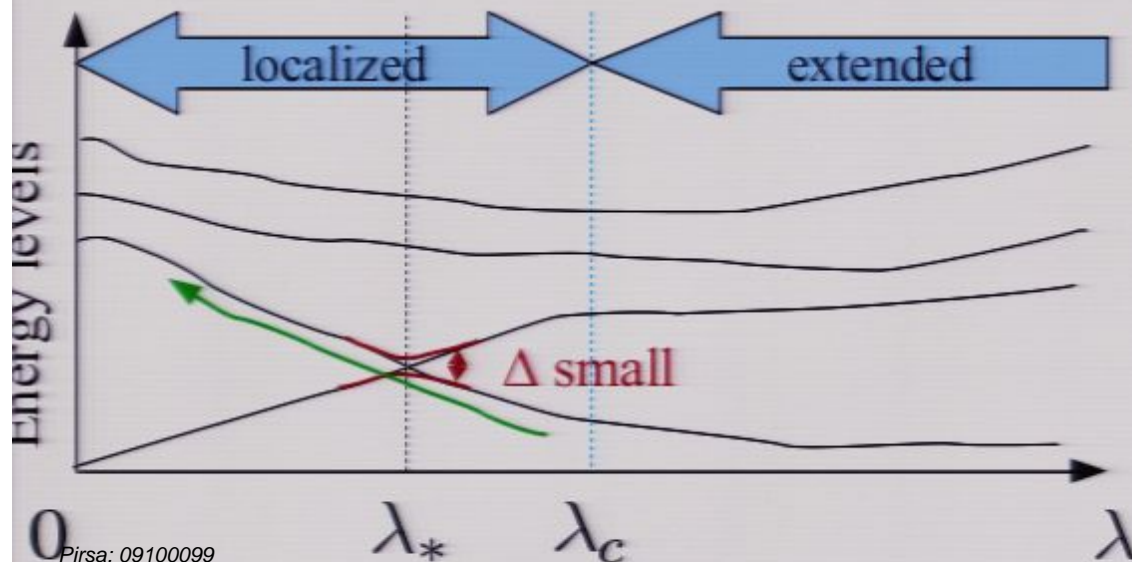
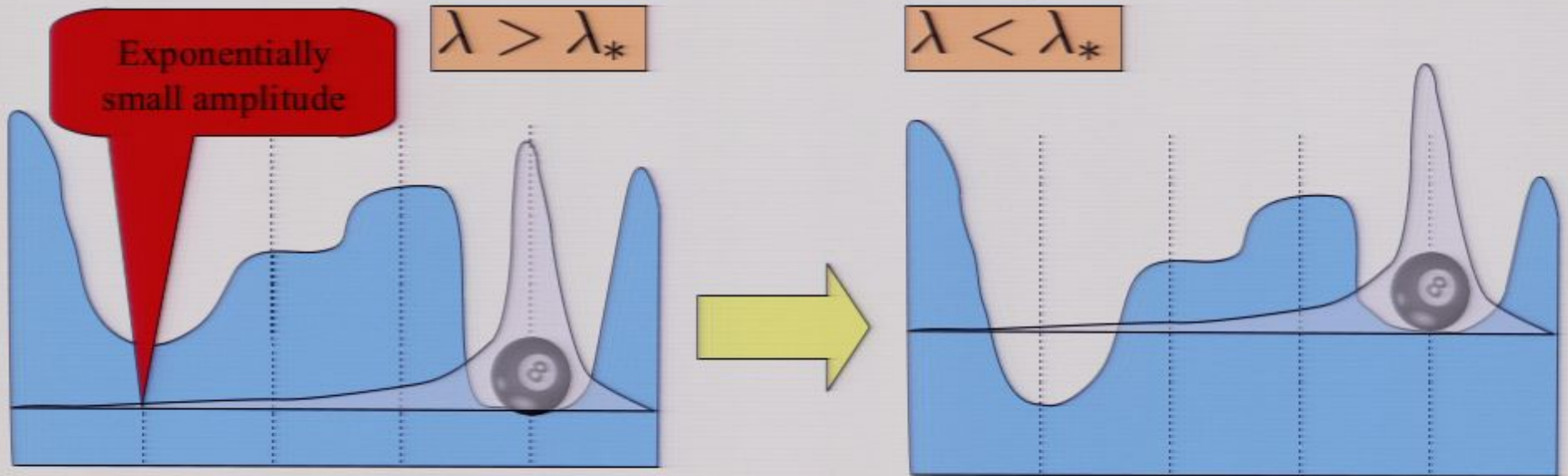
Tunneling: localized state

What if a local minimum later becomes the global minimum?



Tunneling: localized state

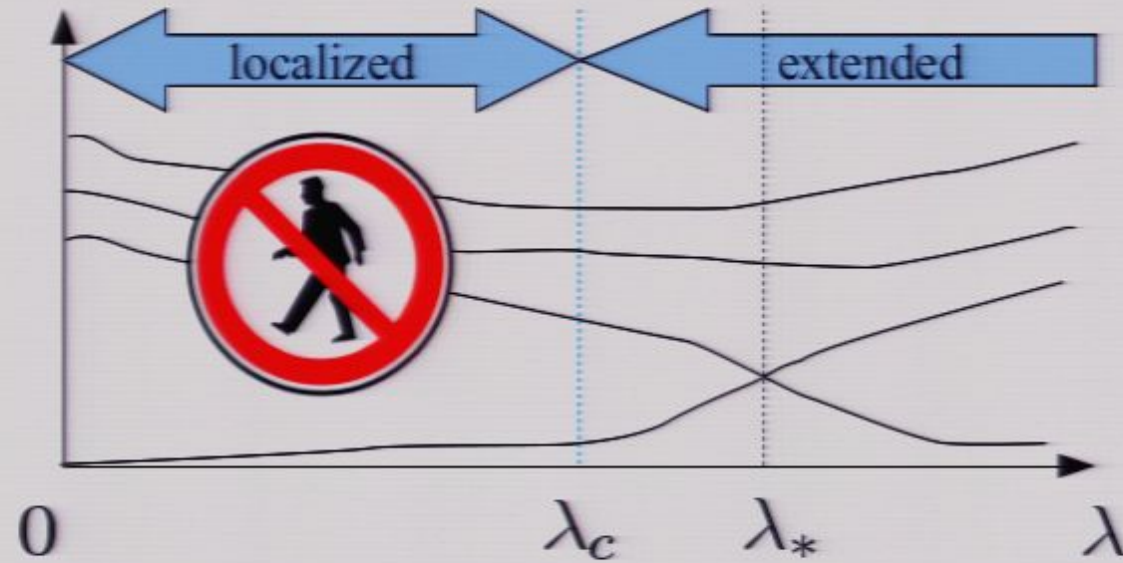
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Small anti-crossing gap
→ Landau-Zener transition

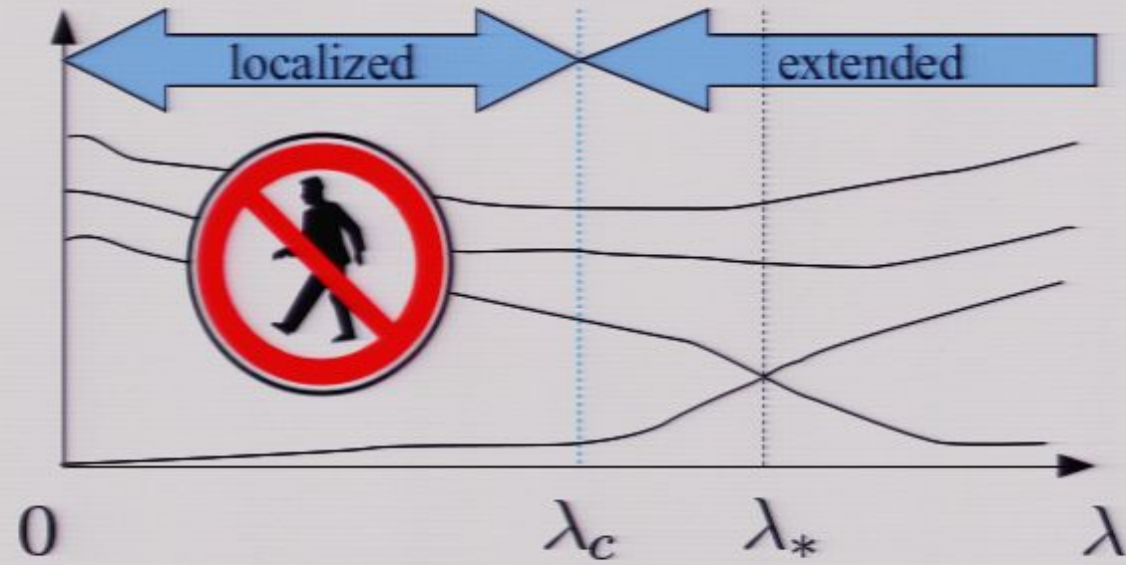


Our result



As the size of the problem N increases

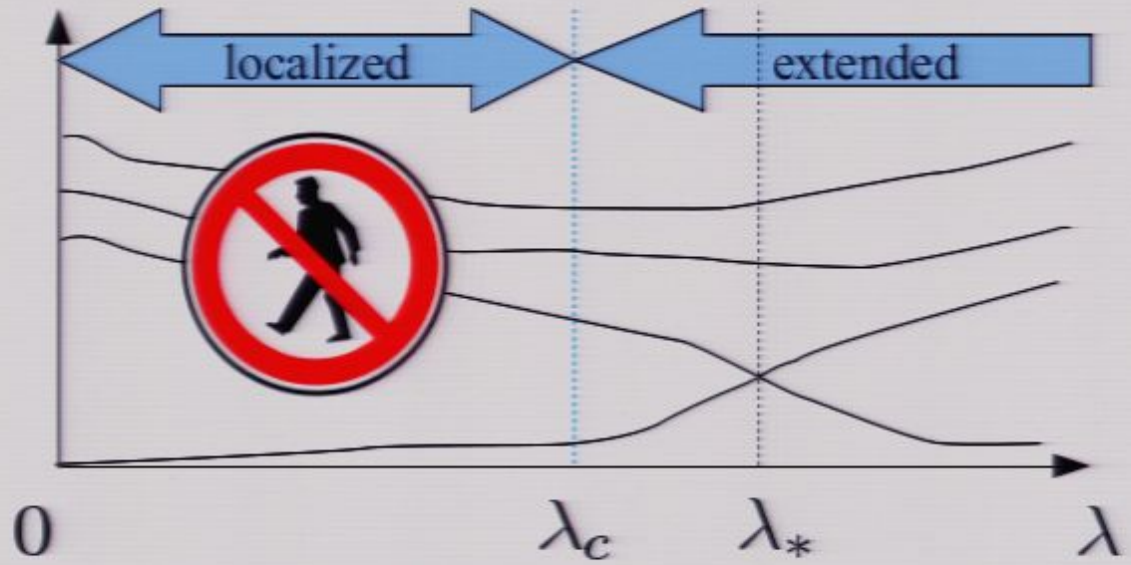
Our result



As the size of the problem N increases

- 1) Anderson localization would imply $\lambda_c = \Omega(1/\log N)$

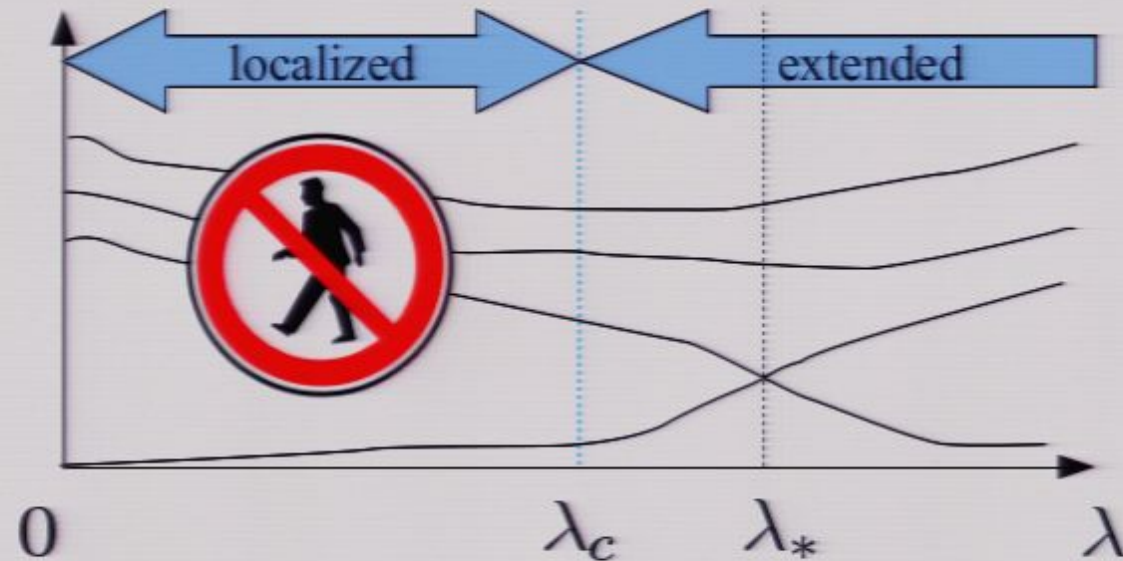
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As the size of the problem N increases

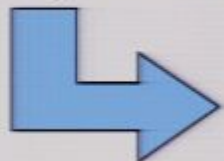
- 1) Anderson localization would imply $\lambda_c = \Omega(1/\log N)$
- 2) Level crossings for smaller and smaller $\lambda_* = (CN)^{-1/8}$

Our result

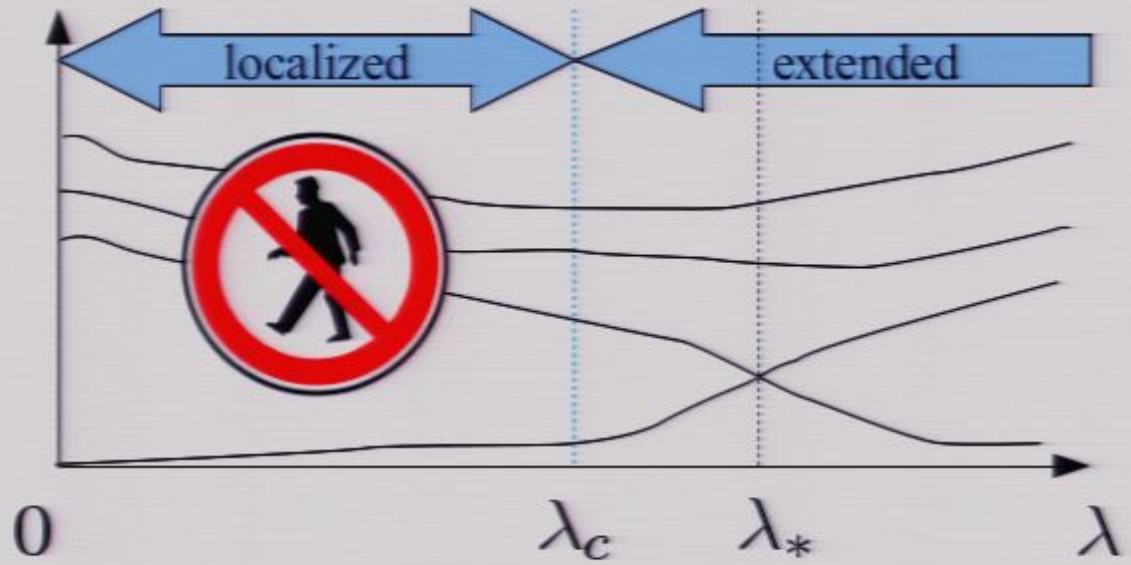


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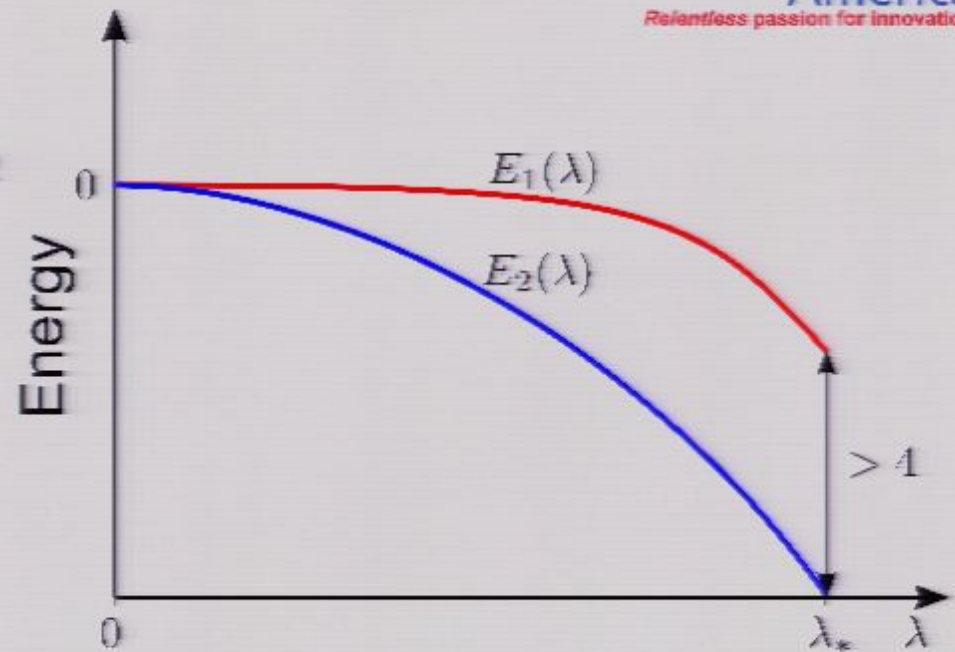
Level crossings

Consider EC3 instance with 2 solutions \vec{x}_1, \vec{x}_2

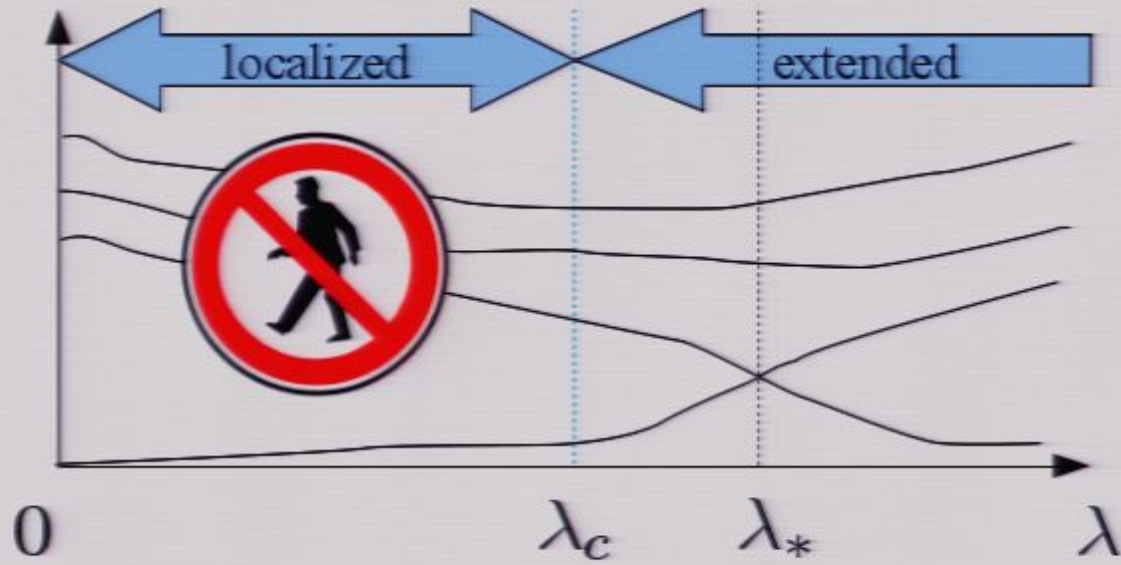
$$E_1(0) = E_2(0) = 0$$

Suppose

$$E_1(\lambda_*) - E_2(\lambda_*) > 4$$



Our result



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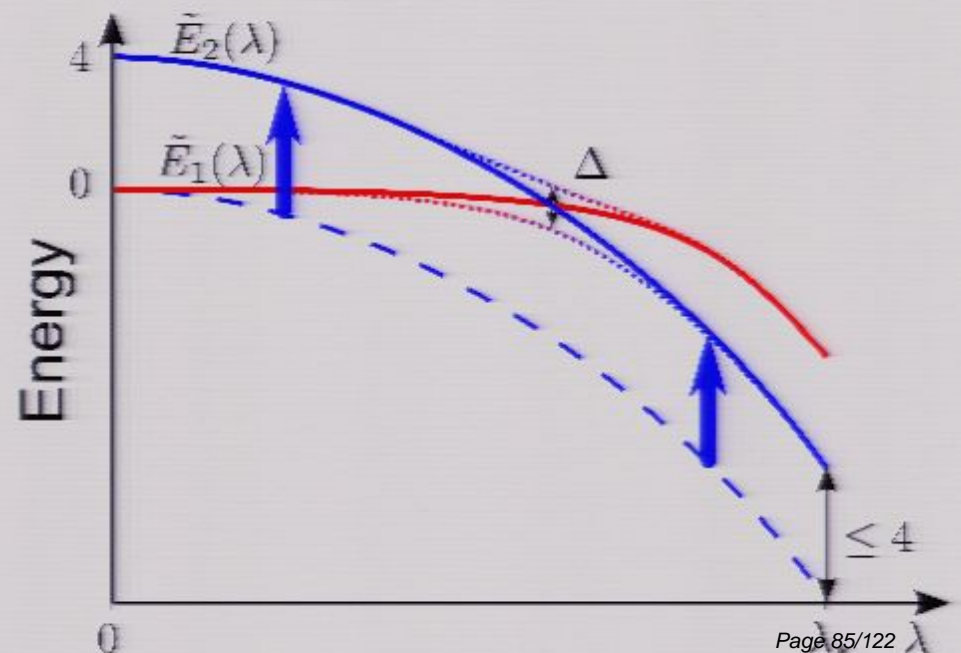
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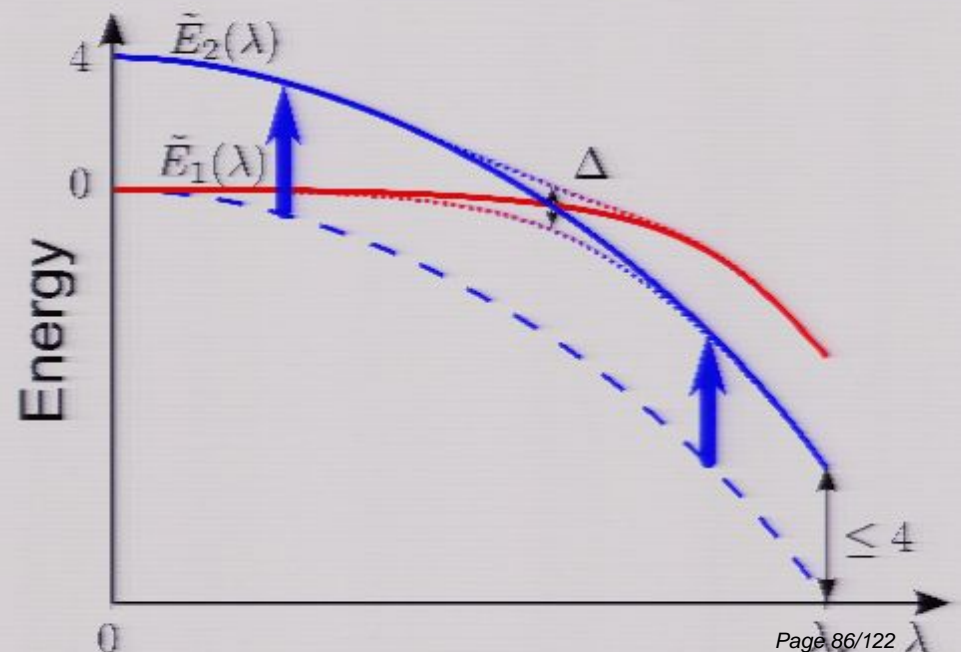
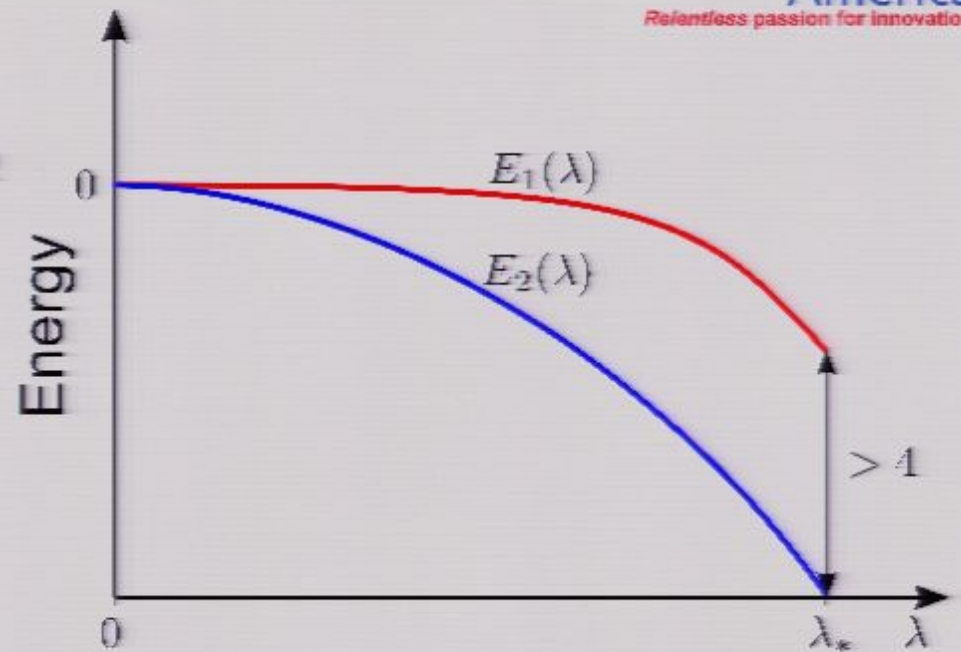
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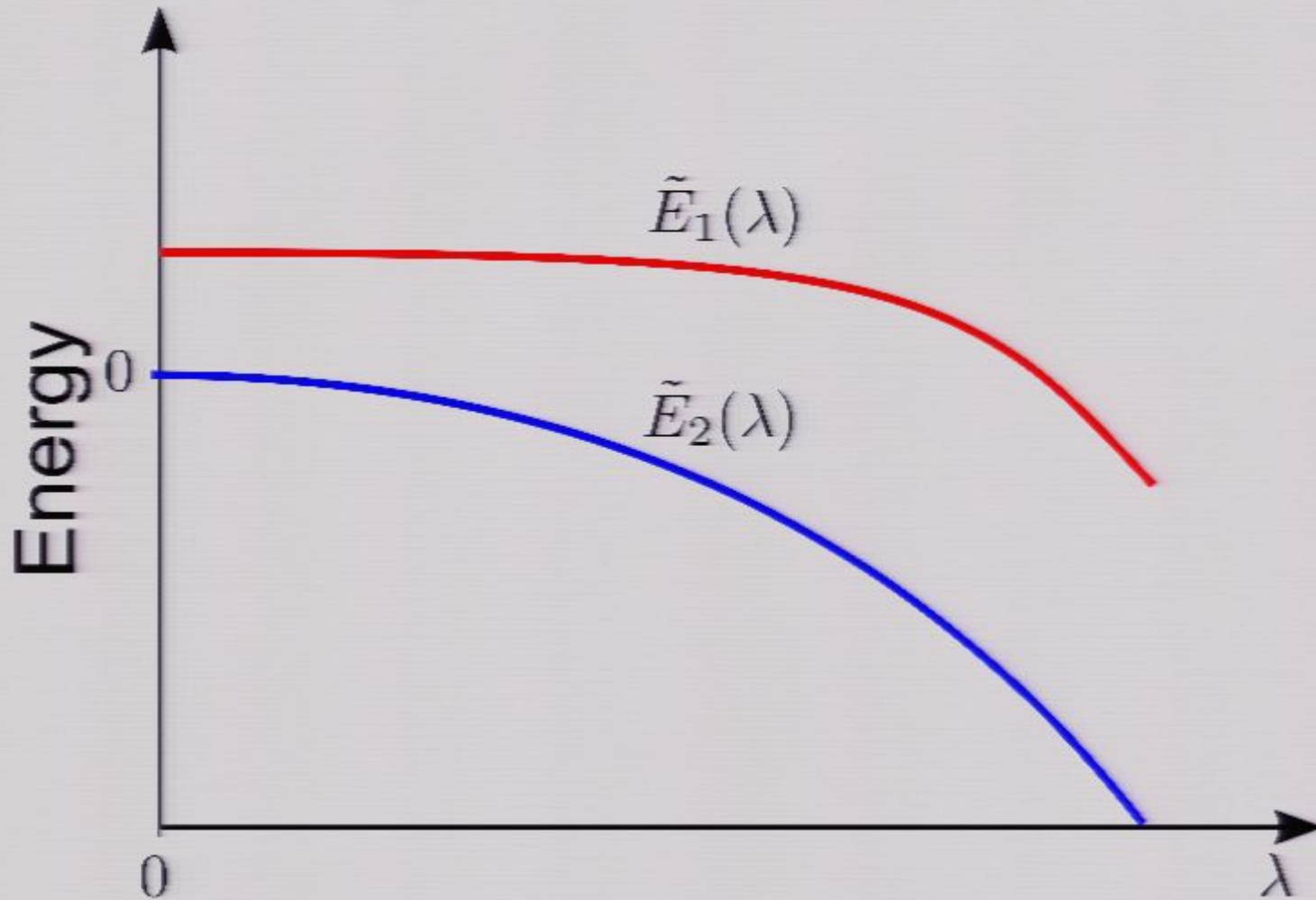
↓
Level crossing

$$d(\vec{x}_1, \vec{x}_2) = n$$

$$\rightarrow \text{Gap } \Delta \sim \lambda_*^n$$



What if the wrong solution is killed?



Level crossings

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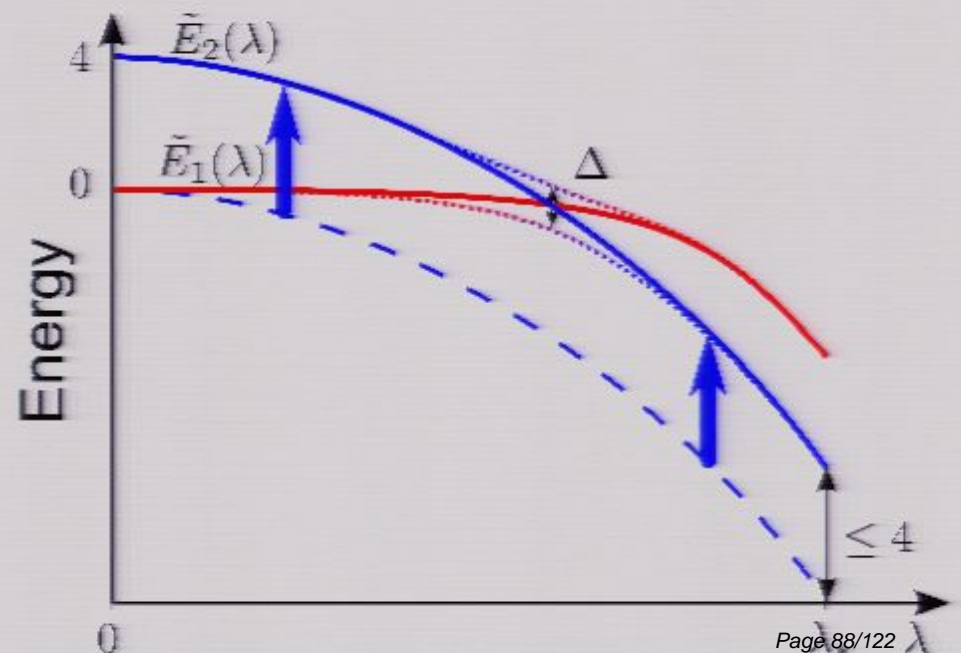
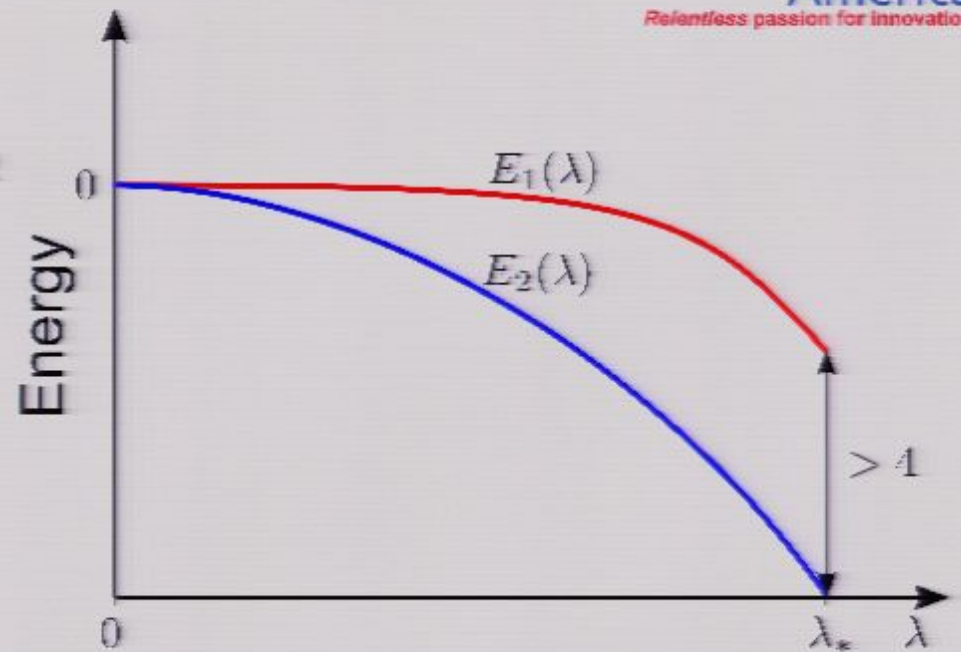
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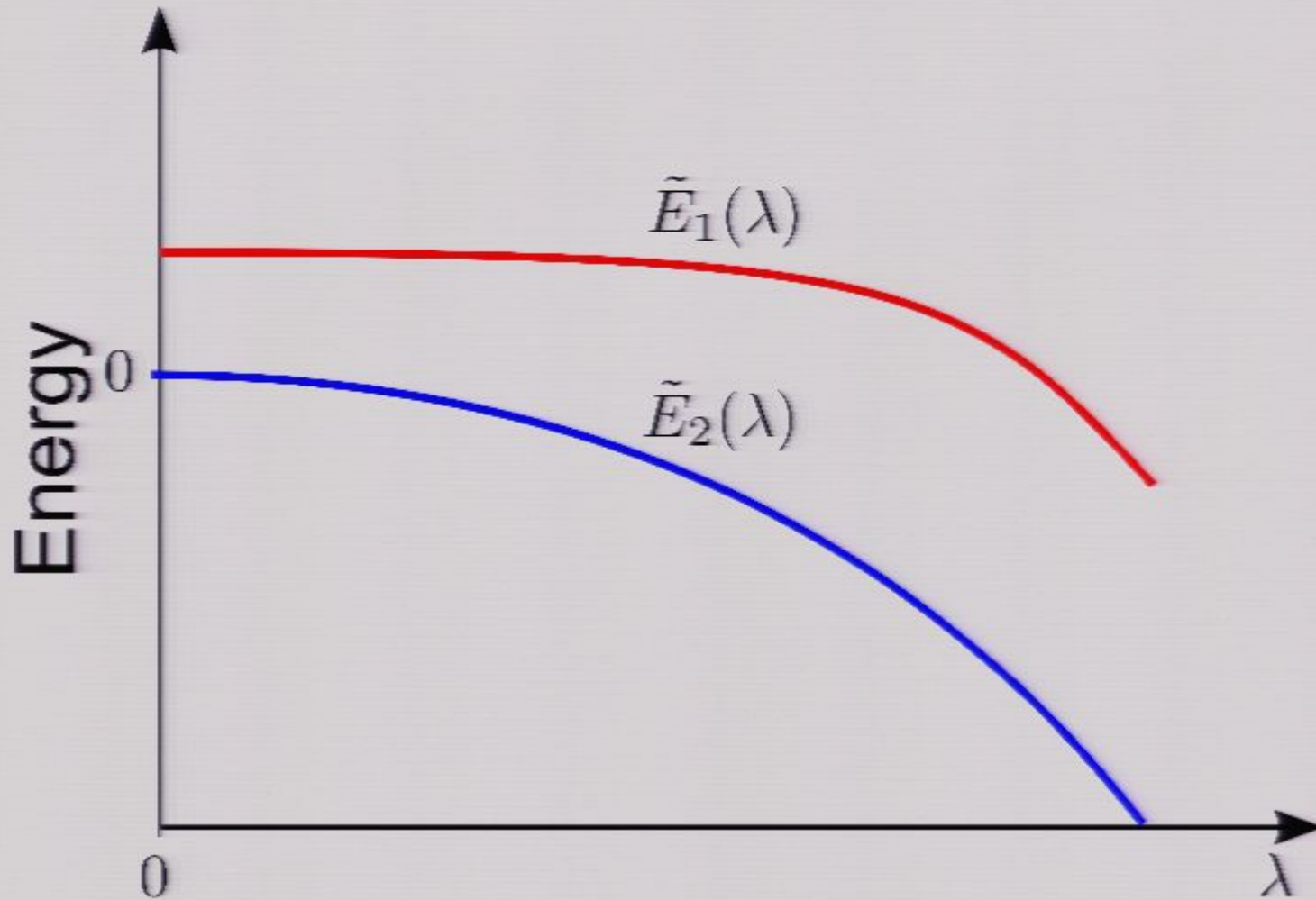
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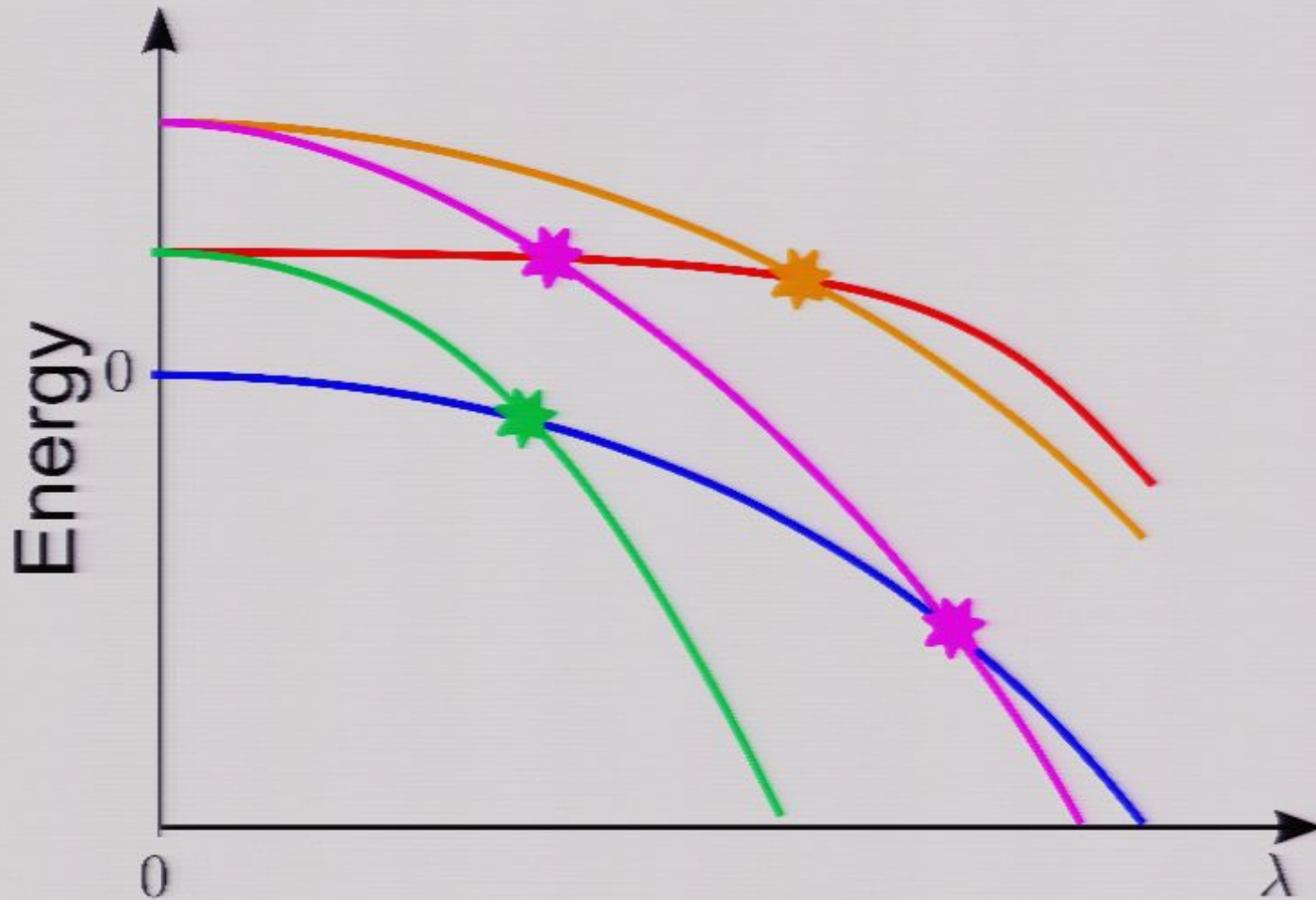
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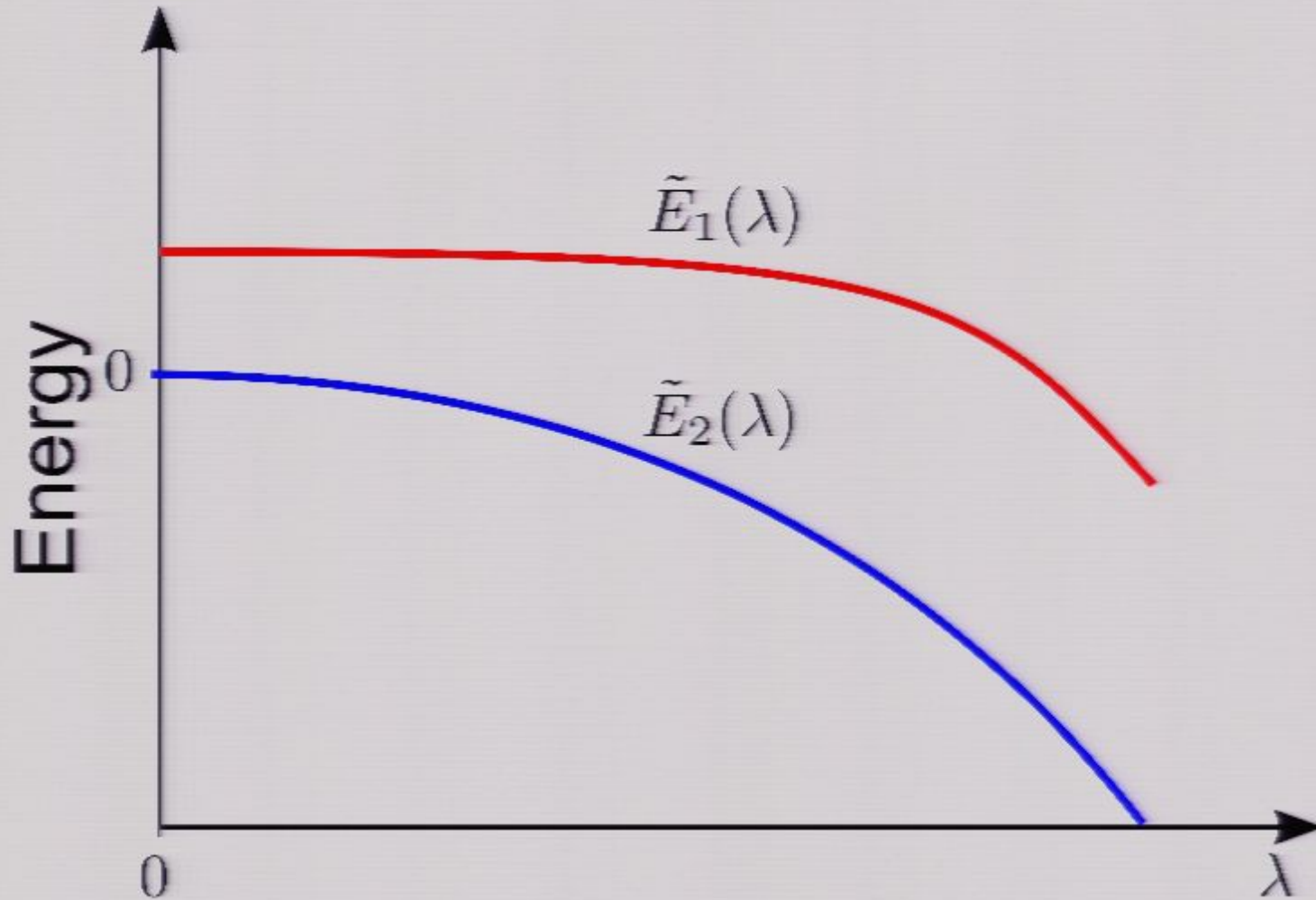
There are crossings with other levels!

Perturbation theory

We compute $E_{\vec{x}}(\lambda)$ by perturbation theory

$$E_{\vec{x}}(\lambda) = E_{\vec{x}}(0) + \sum_{m=1}^{\infty} \lambda^{2m} F_{\vec{x}}^{(m)}$$

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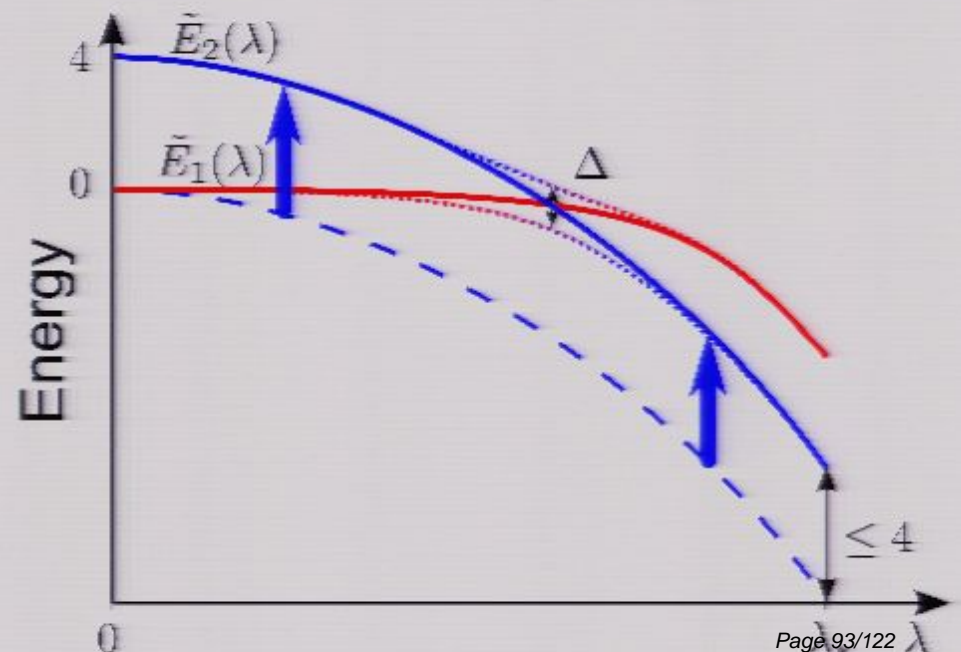
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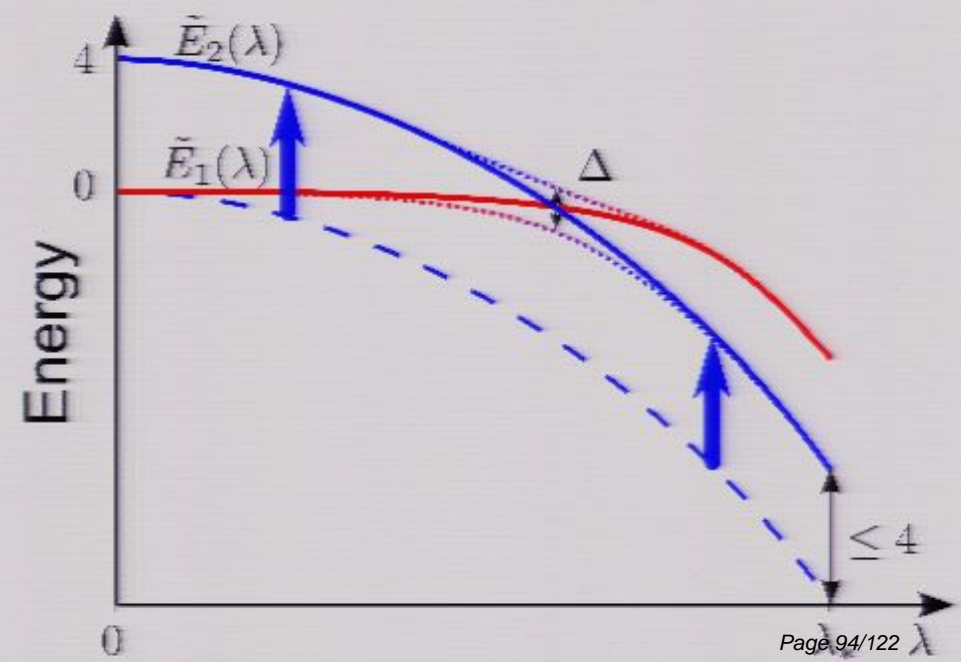
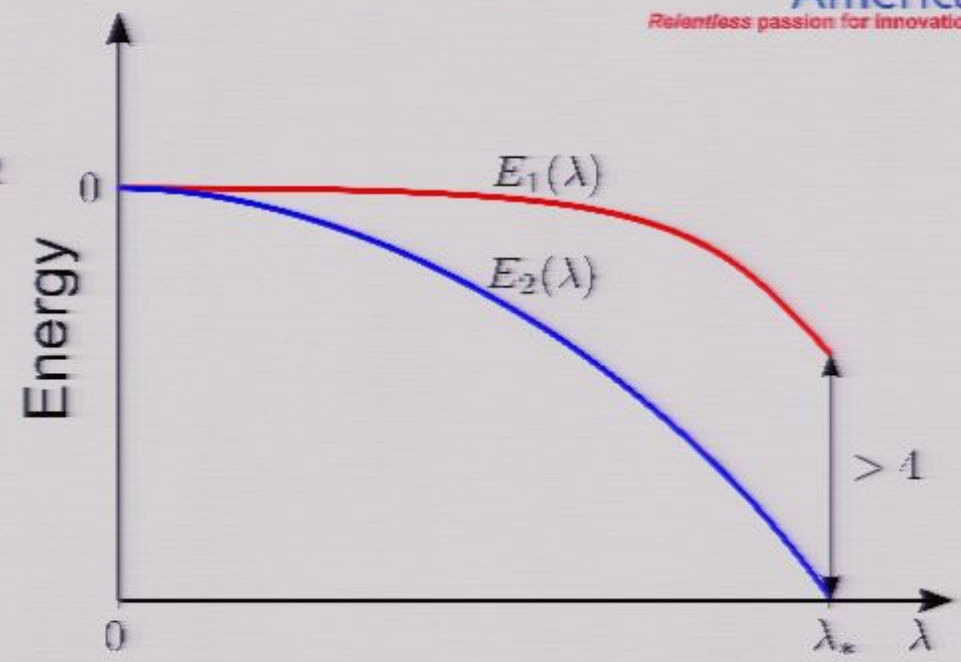
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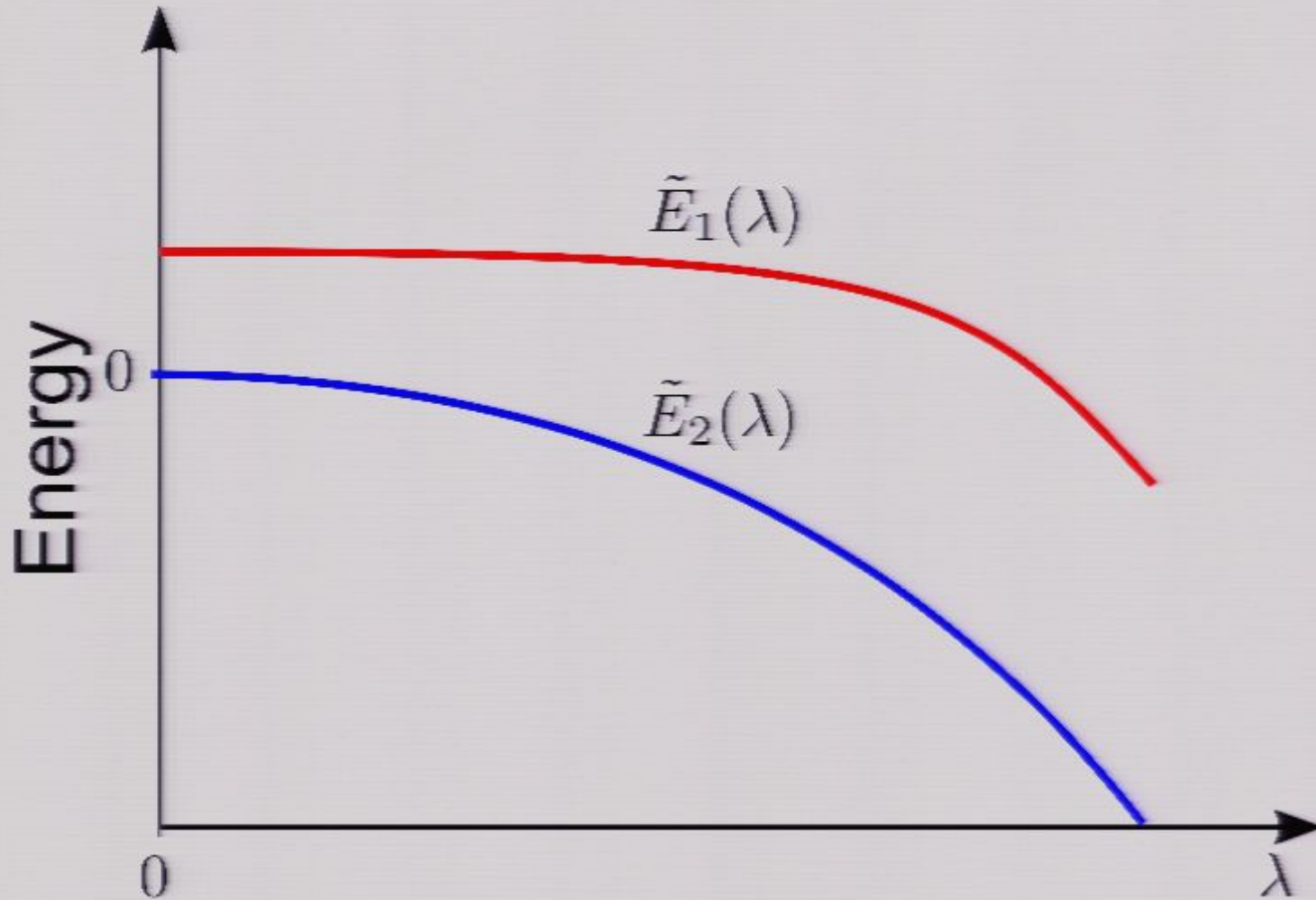

Level crossing

$$d(\vec{x}_1, \vec{x}_2) = n$$

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We prove:

$$F_{\vec{x}}^{(m)} = O(N) \quad \forall m$$

Proof based on statistical
properties of random instances

Perturbation theory

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We prove:

$$F_{\vec{x}}^{(m)} = O(N) \quad \forall m$$

For 2 solutions, the difference has zero mean, so

$$(F_1^{(m)} - F_2^{(m)})^2 = O(N) \quad \forall m$$

Numerical simulations

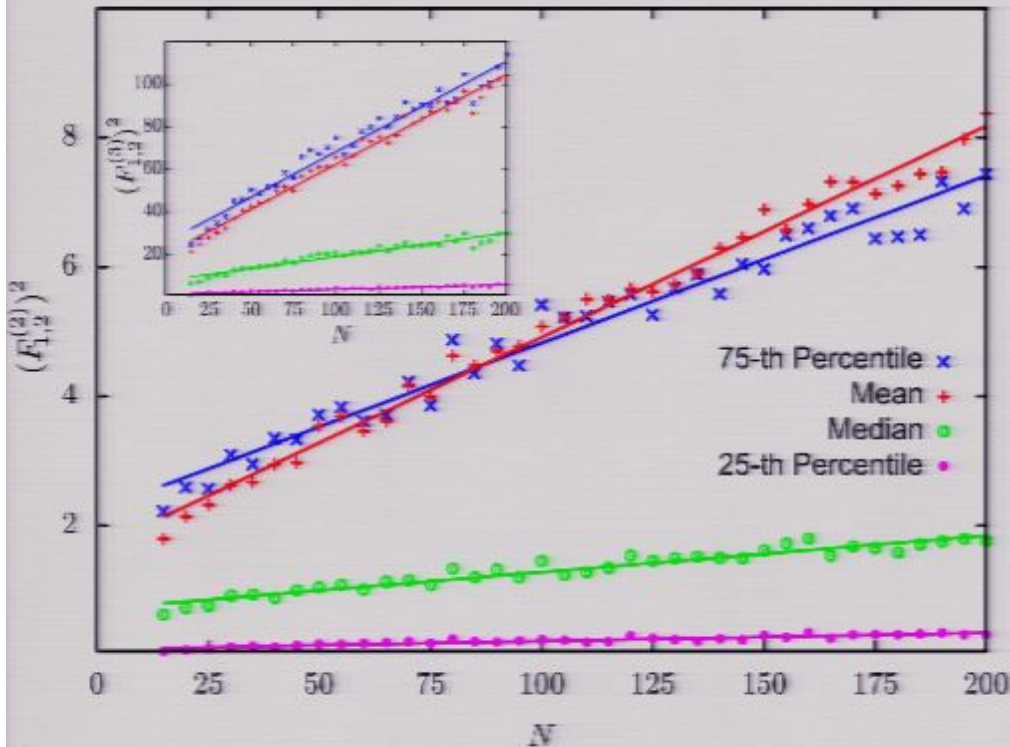
- We generated EC3 random instances with >2 solutions
- then computed $E_1(\lambda) - E_2(\lambda)$ by order 4 perturbation theory

Leading order because:

- Odd orders are zero
- Order 2 is solution-independent for EC3

Numerical simulations

- We generated EC3 random instances with >2 solutions
- then computed $E_1(\lambda) - E_2(\lambda)$ by order 4 perturbation theory

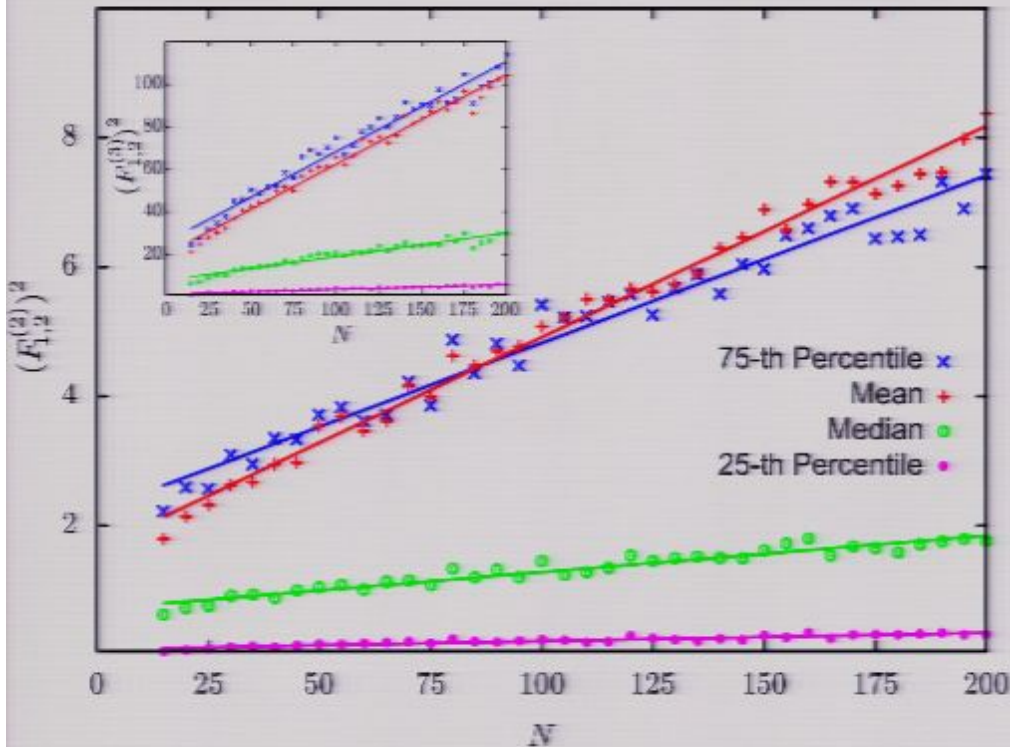


Each data point computed from 2500 instances

$$(E_1(\lambda) - E_2(\lambda))^2 \approx CN\lambda^8$$

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We have $E_1(\lambda) - E_2(\lambda) > 4$ for $\lambda > \sqrt{2}(CN)^{-1/8}$

How small is the gap?

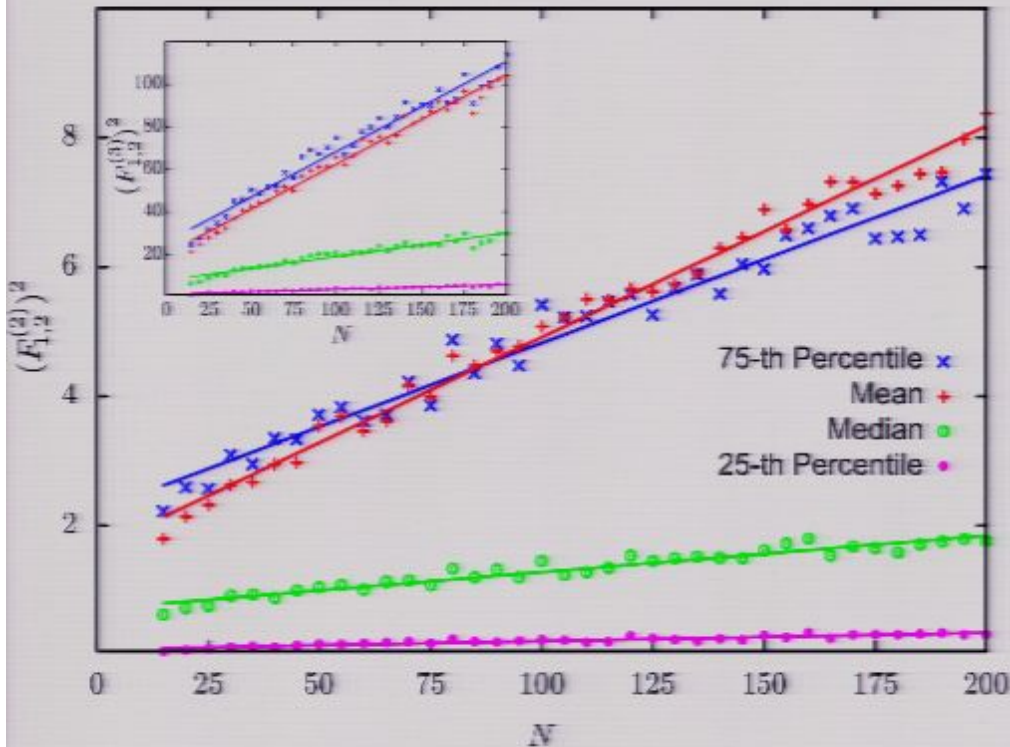
We show that up to leading order in perturbation theory:

$$\Delta < (2\lambda_*)^n$$

Proof by reduction to the “Agree” problem:
2-bit clauses $(x_{i_C} = x_{j_C})$

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Each data point computed from 2500 instances

$$(E_1(\lambda) - E_2(\lambda))^2 \approx CN\lambda^8$$

We have $E_1(\lambda) - E_2(\lambda) > 4$ for $\lambda > \sqrt{2}(CN)^{-1/8}$

How small is the gap?

We show that up to leading order in perturbation theory:

$$\Delta < (2\lambda_*)^n$$

Proof by reduction to the “Agree” problem:
2-bit clauses $(x_{i_C} = x_{j_C})$

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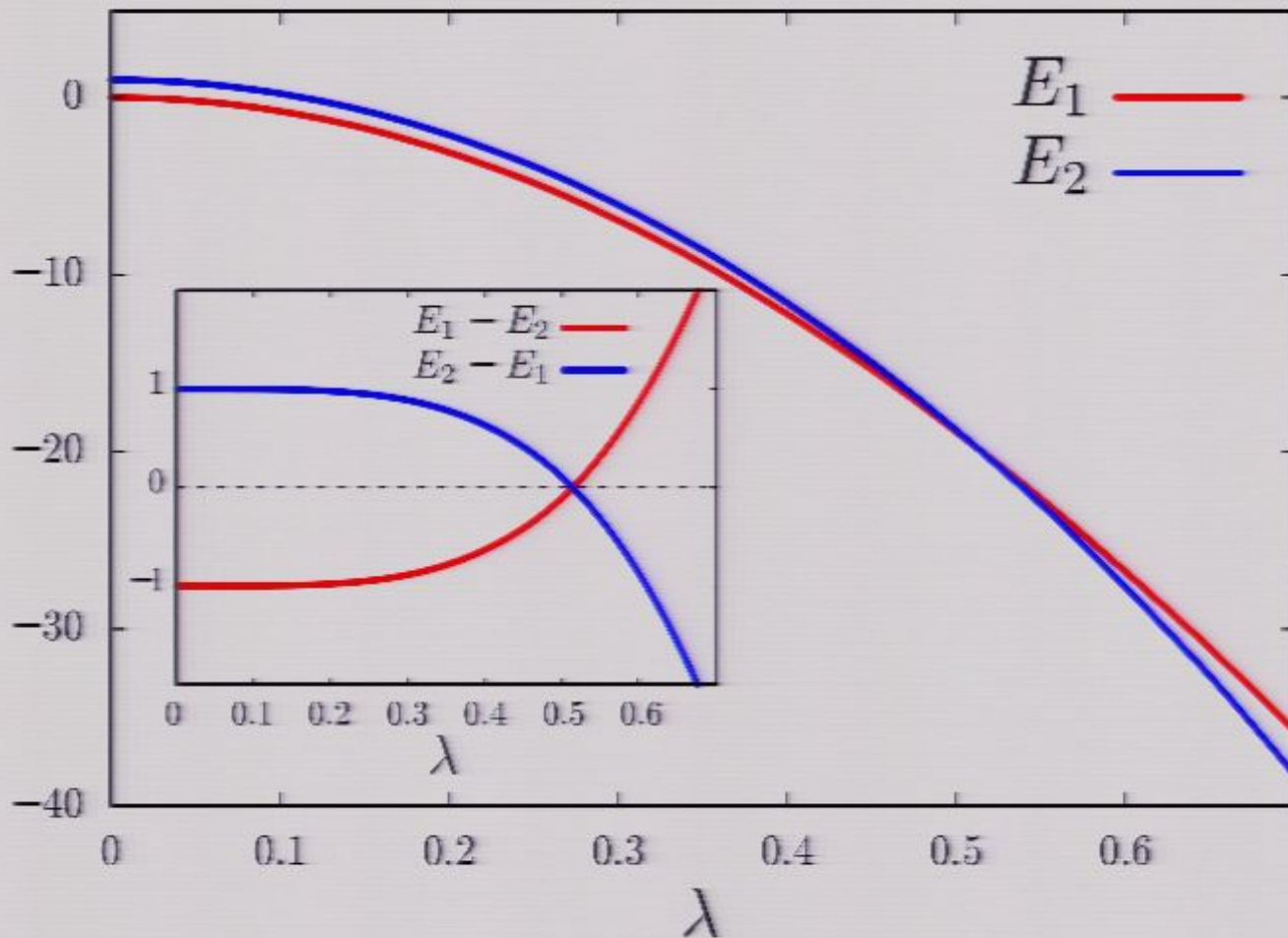
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We have: $\Delta = O(\exp(-N \log N))$

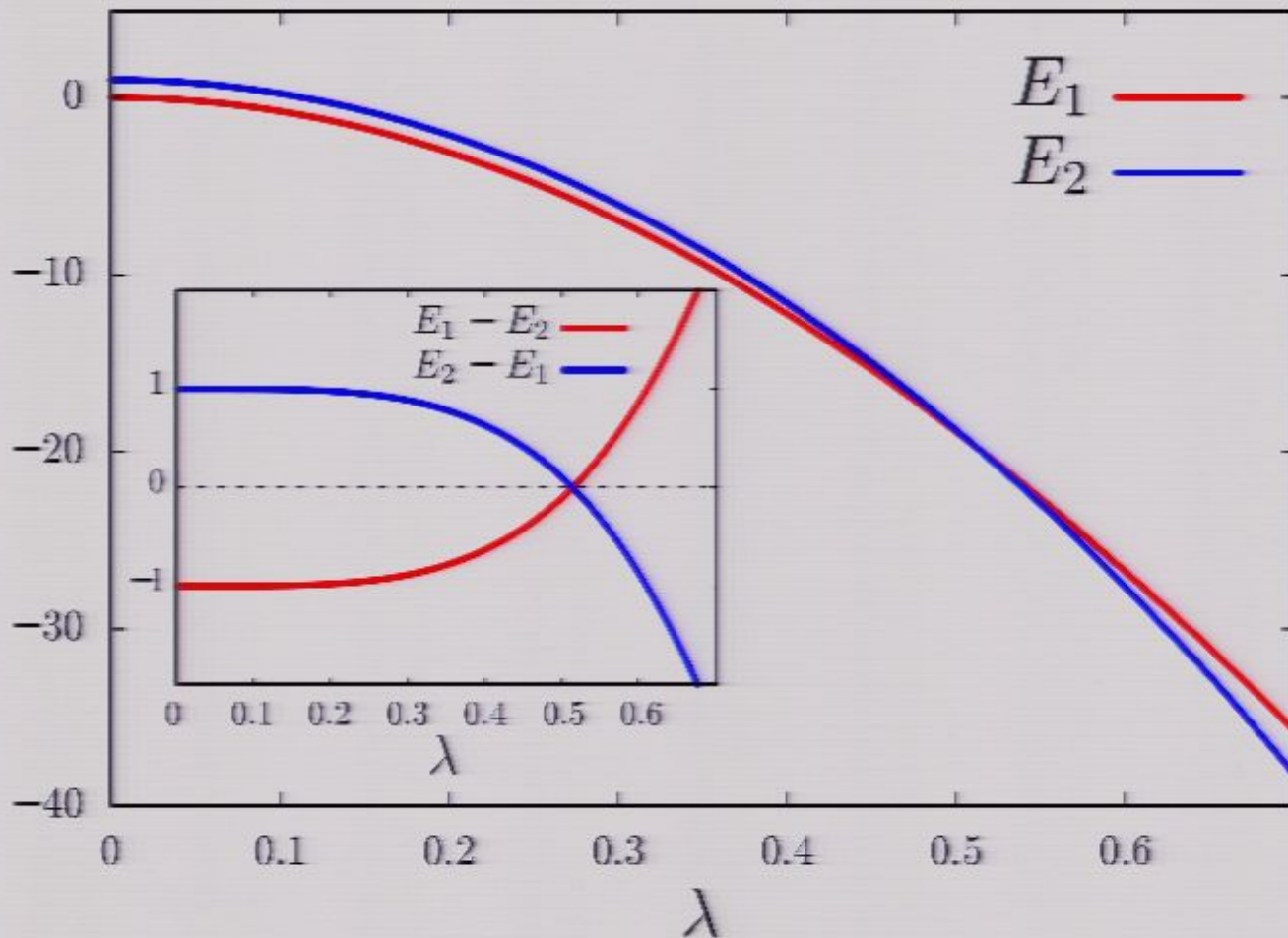
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Simulation of an anti-crossing by 4th order perturbation theory:

- Number of bits: $N = 200$
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Anderson localization theory

⇒ Perturbation theory valid as long as states are localized

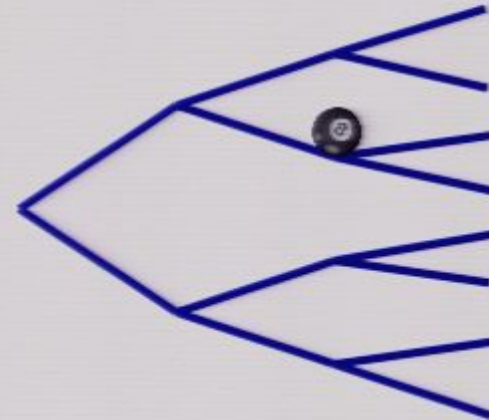
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$$\lambda_c = \Theta \left(\frac{E}{K \log K} \right)$$



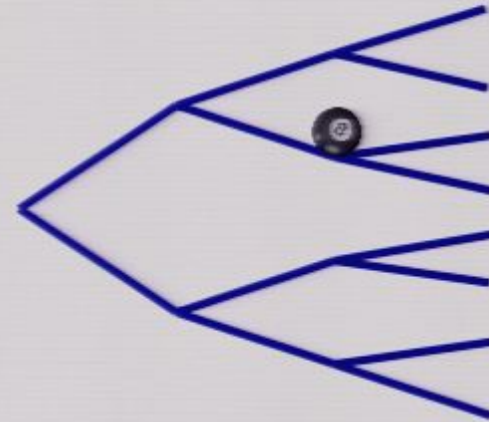
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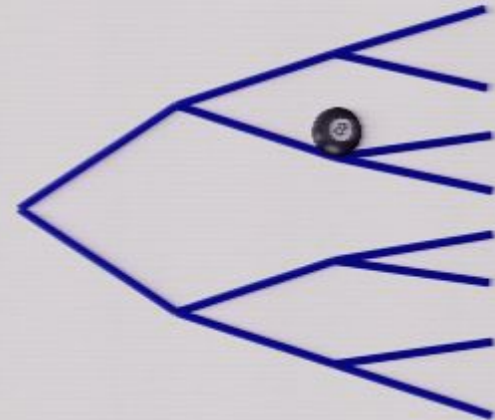
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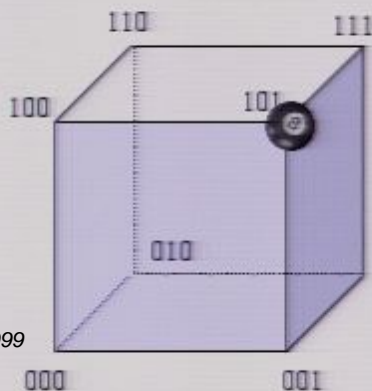
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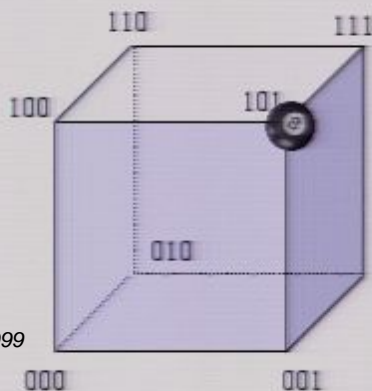
Conclusion

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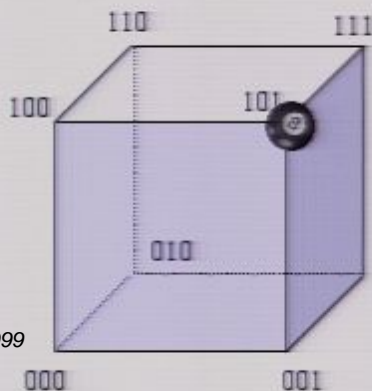
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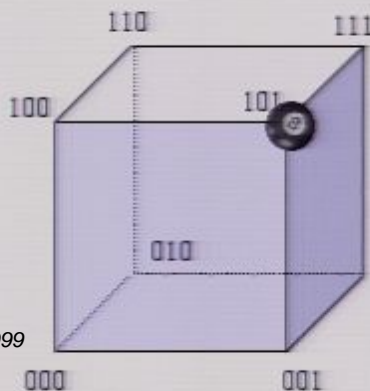
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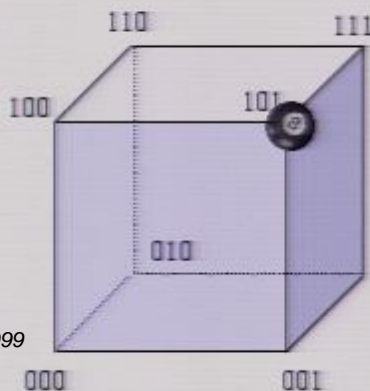
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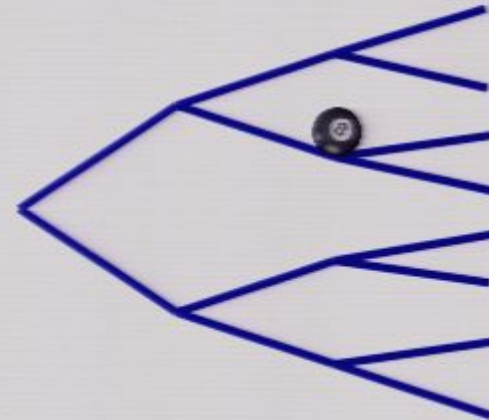
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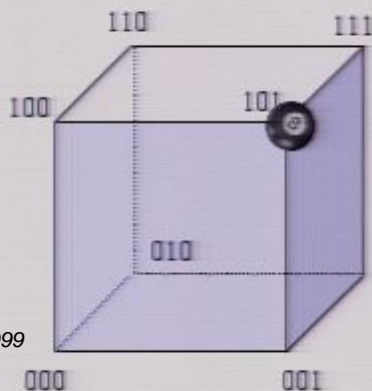
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