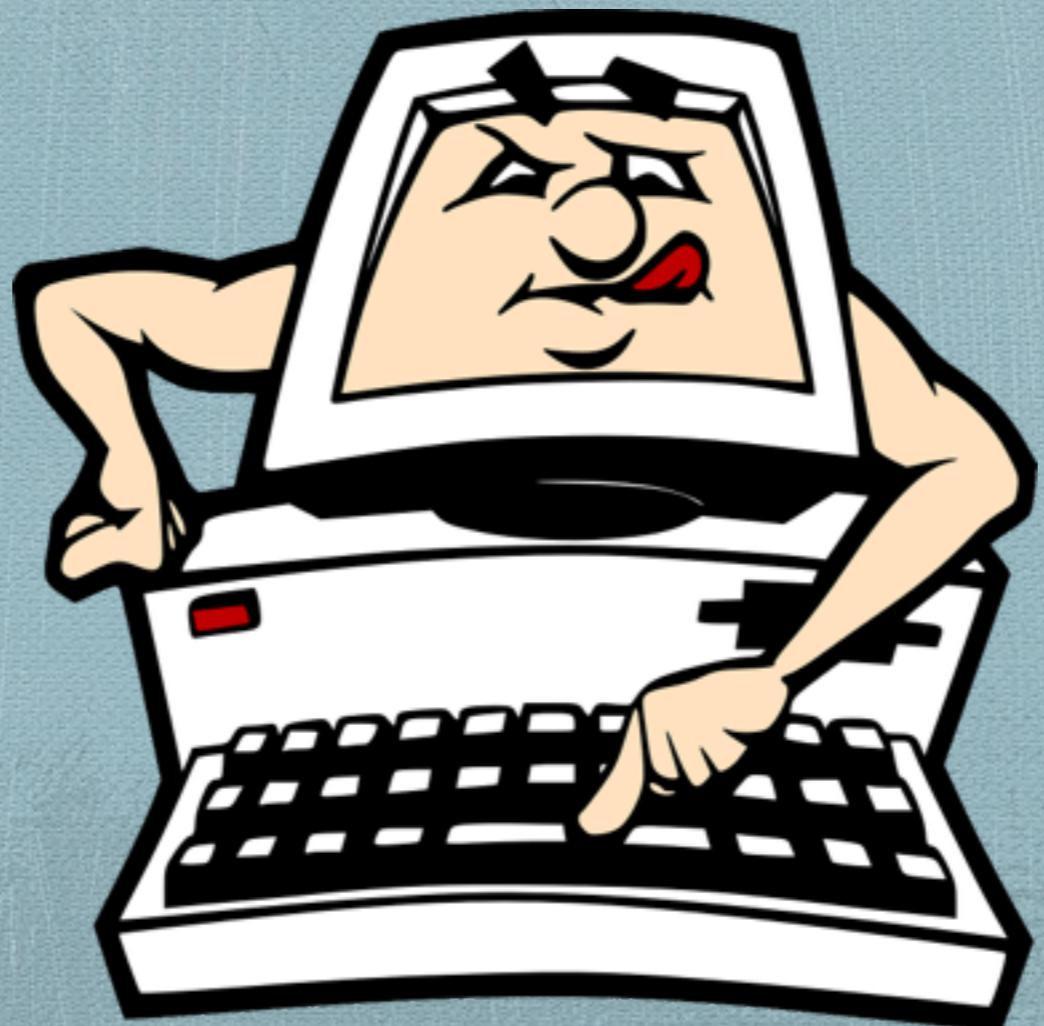


# Black-box Separations for Differentially Private Protocols

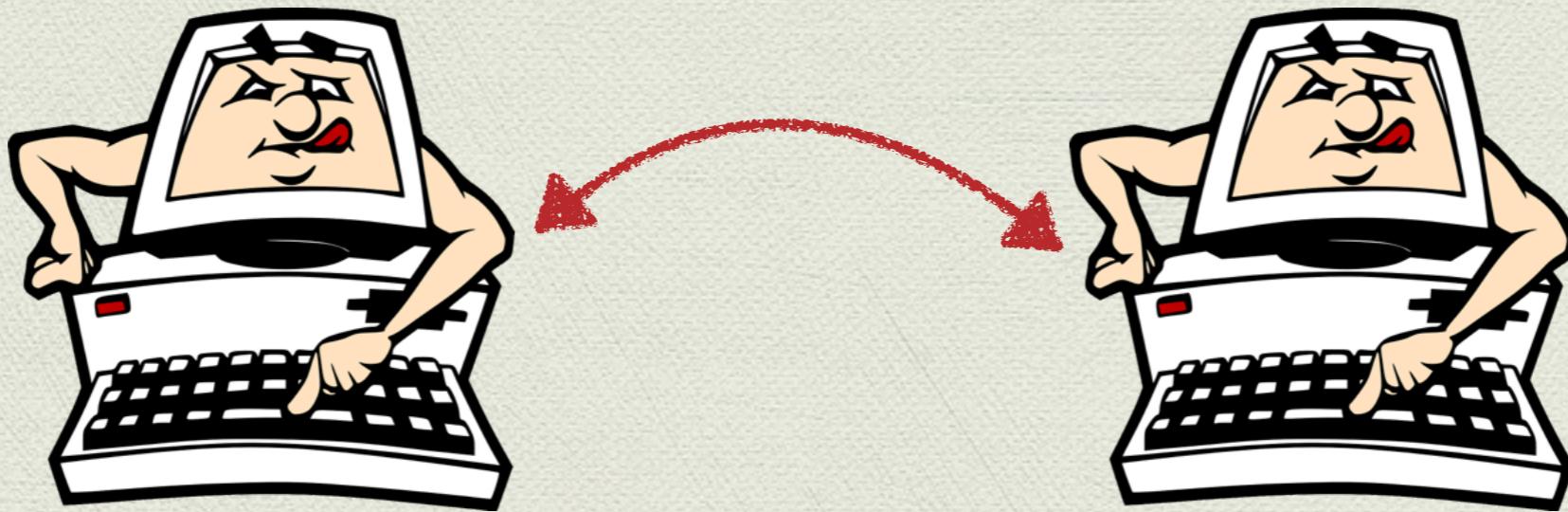
Dakshita Khurana, Hemanta K. Maji, Amit Sahai



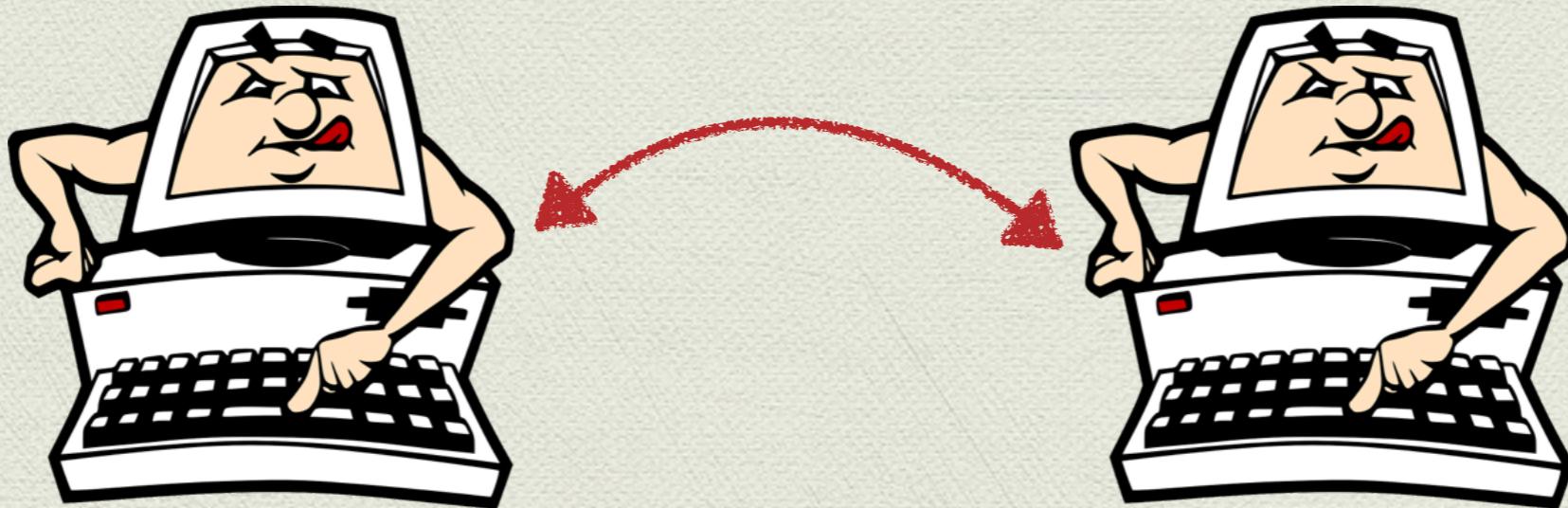
# The Setting

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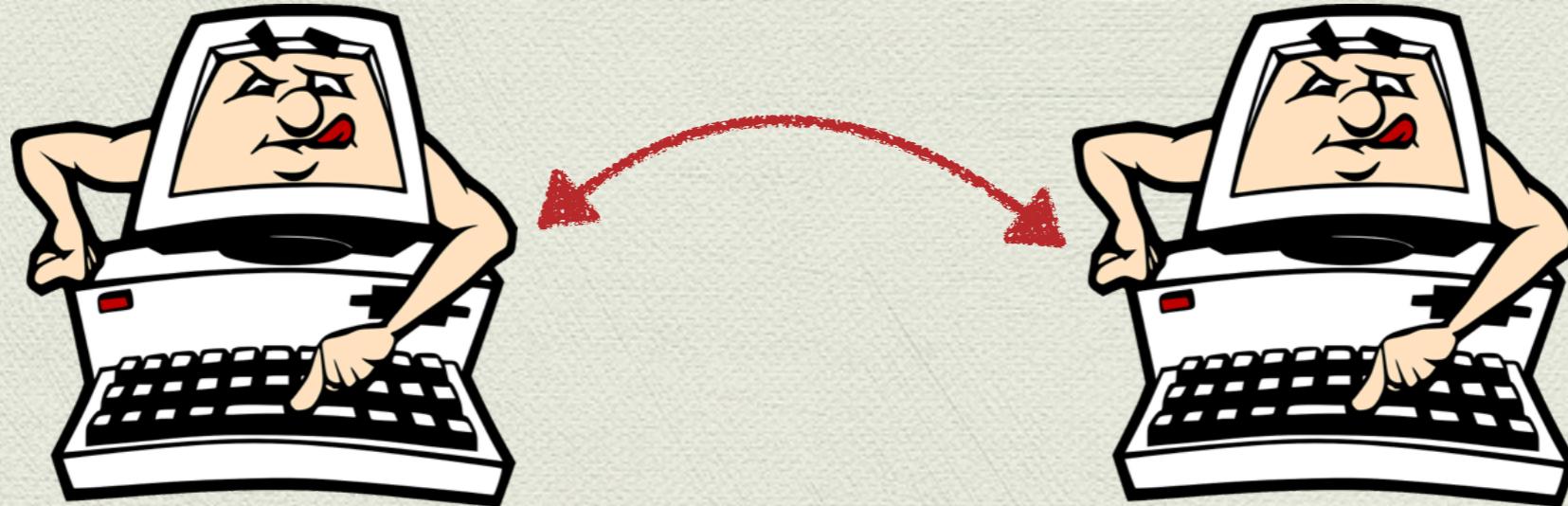
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Differential  
Privacy

# Differential Privacy

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[Dwork '11]

[DN'04, BDMN '05, DMNS '06]

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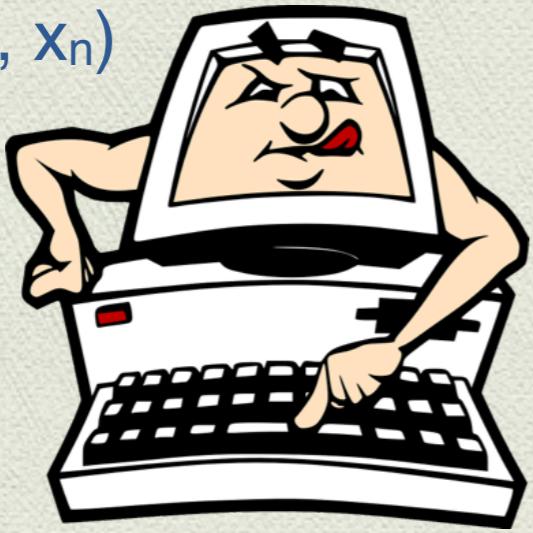


[DN'04, BDMN '05, DMNS '06]

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[Dwork '11]

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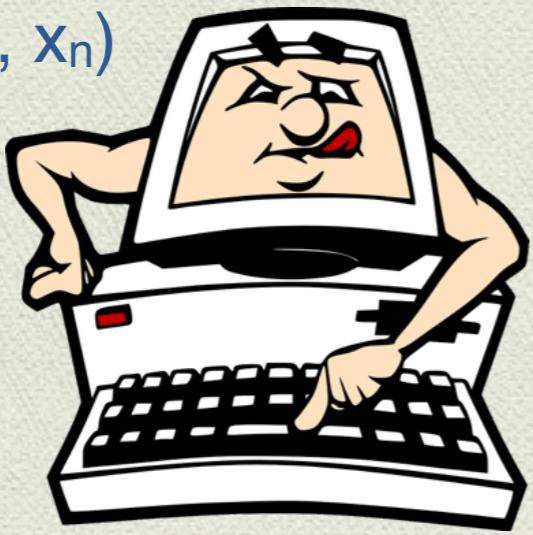


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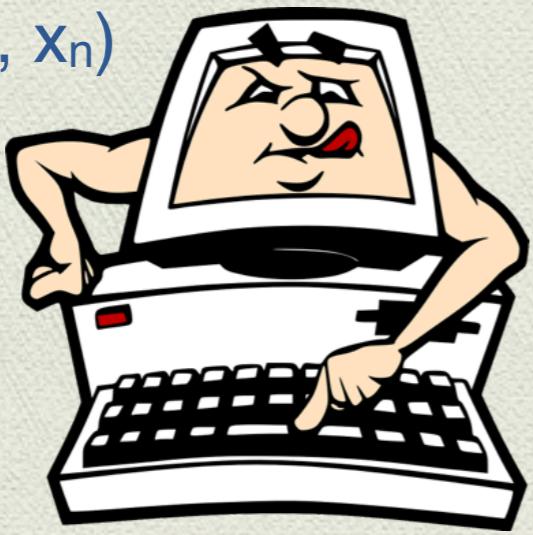


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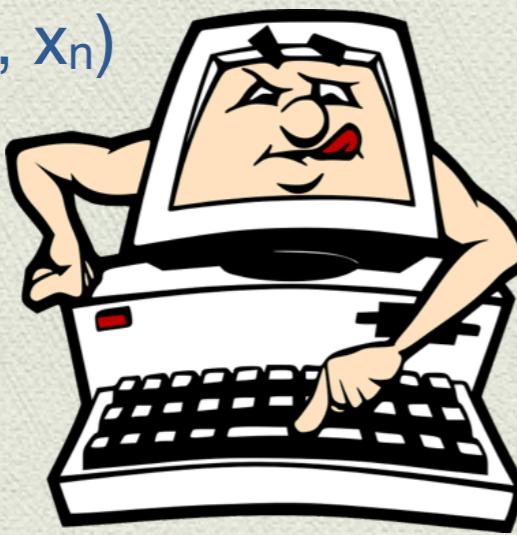


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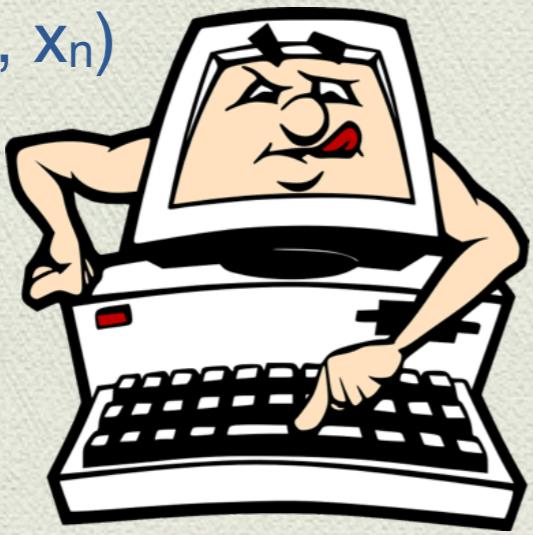


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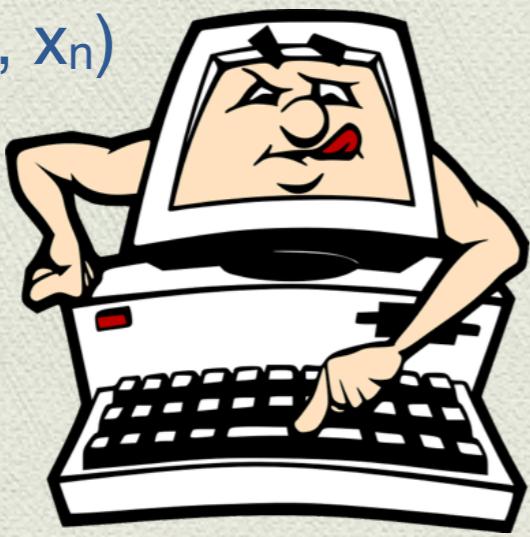
$f'(d) = f(d) + \text{noise}$

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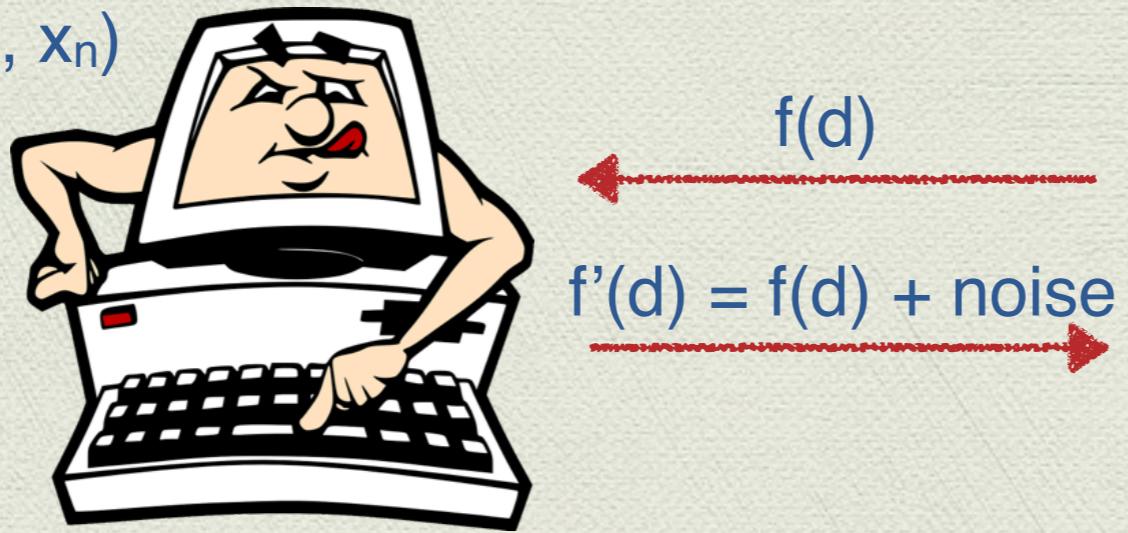


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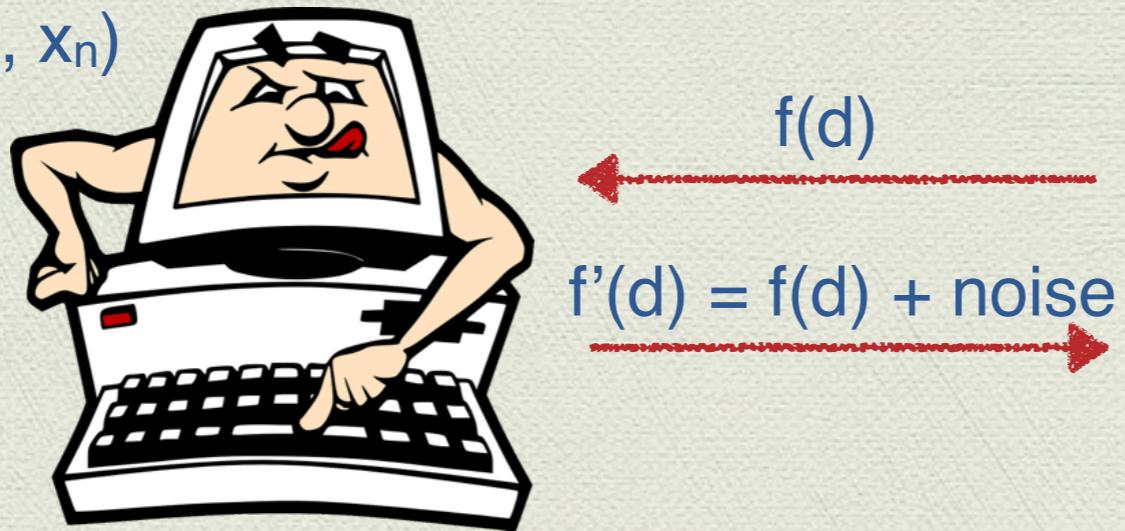
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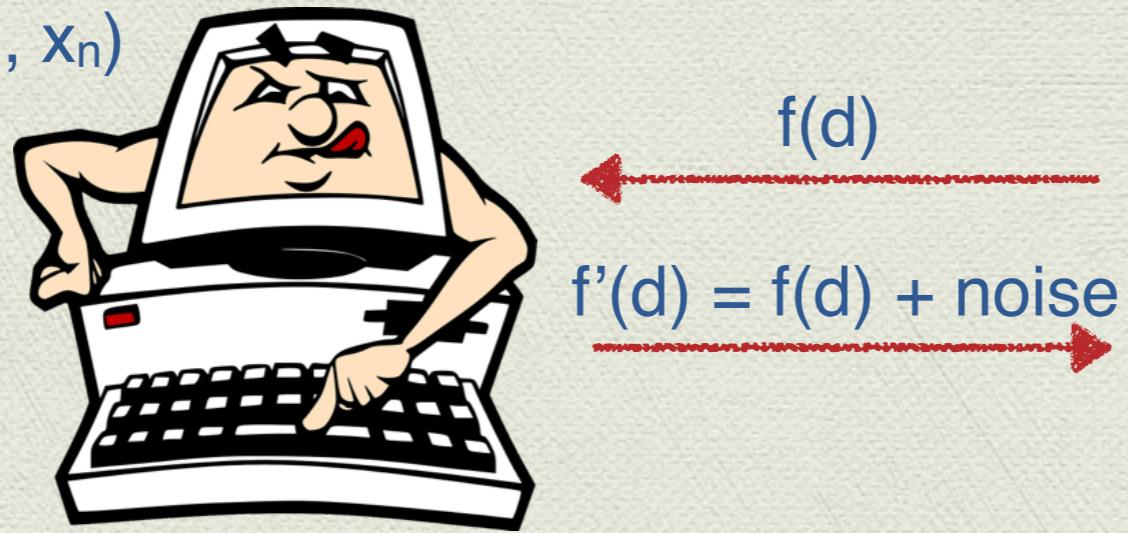
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# Differential Privacy

[Dwork '11]

( $\epsilon$ ,  $\alpha$ ) DP Protocol in Client-Server Setting

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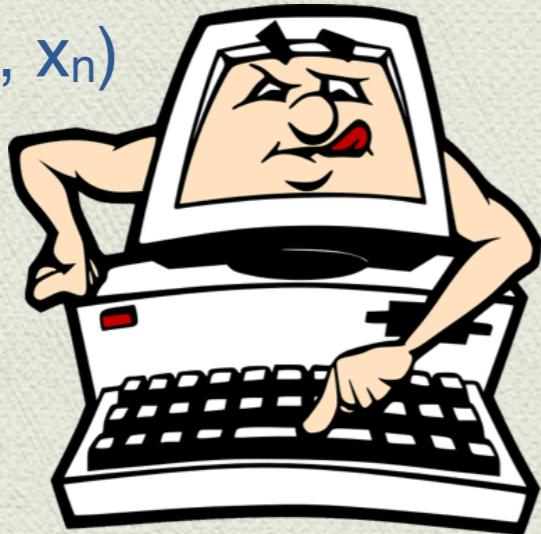


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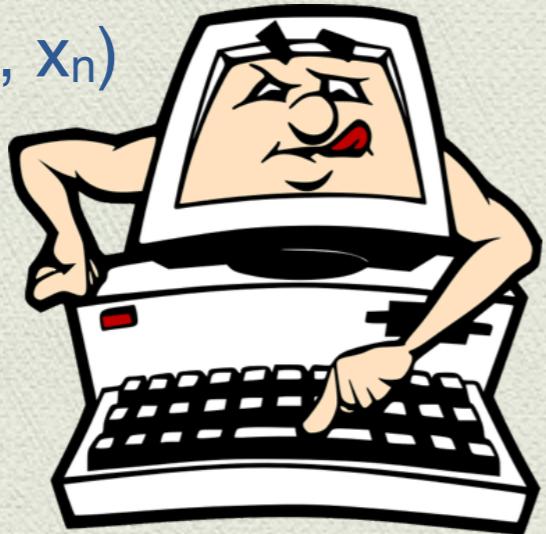


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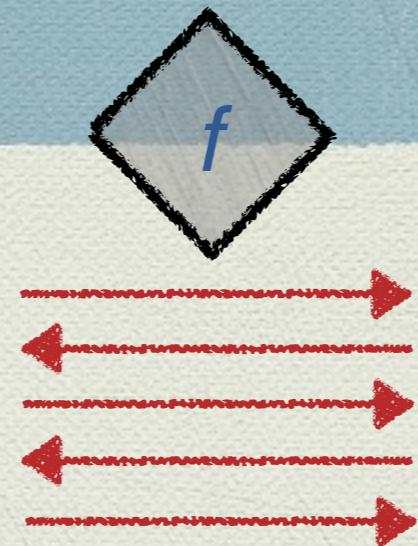
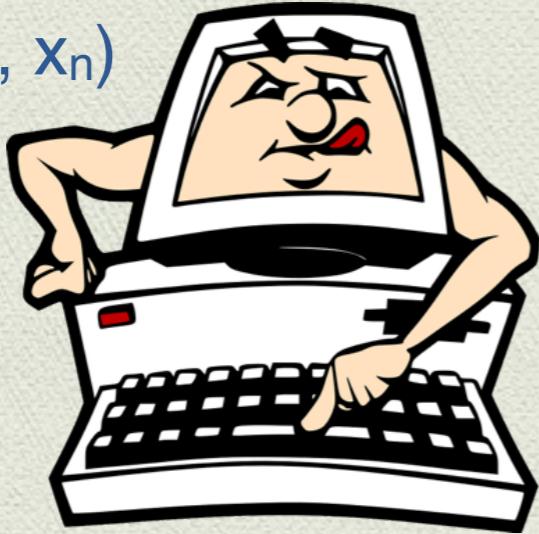
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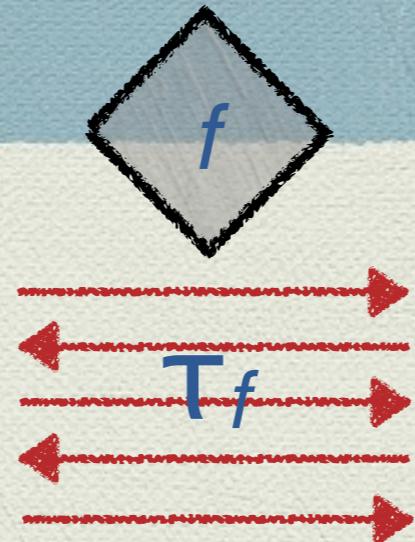
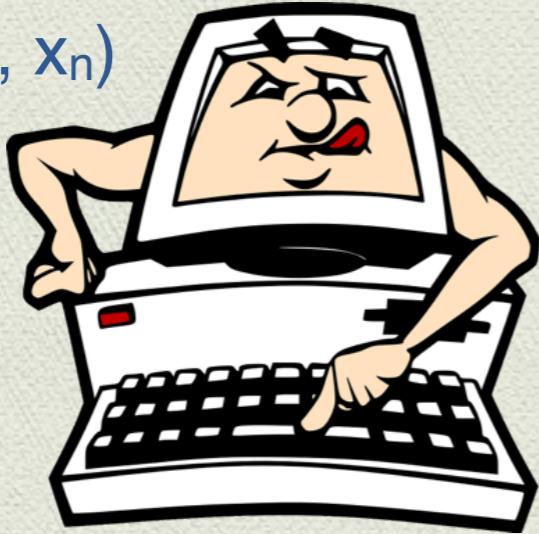
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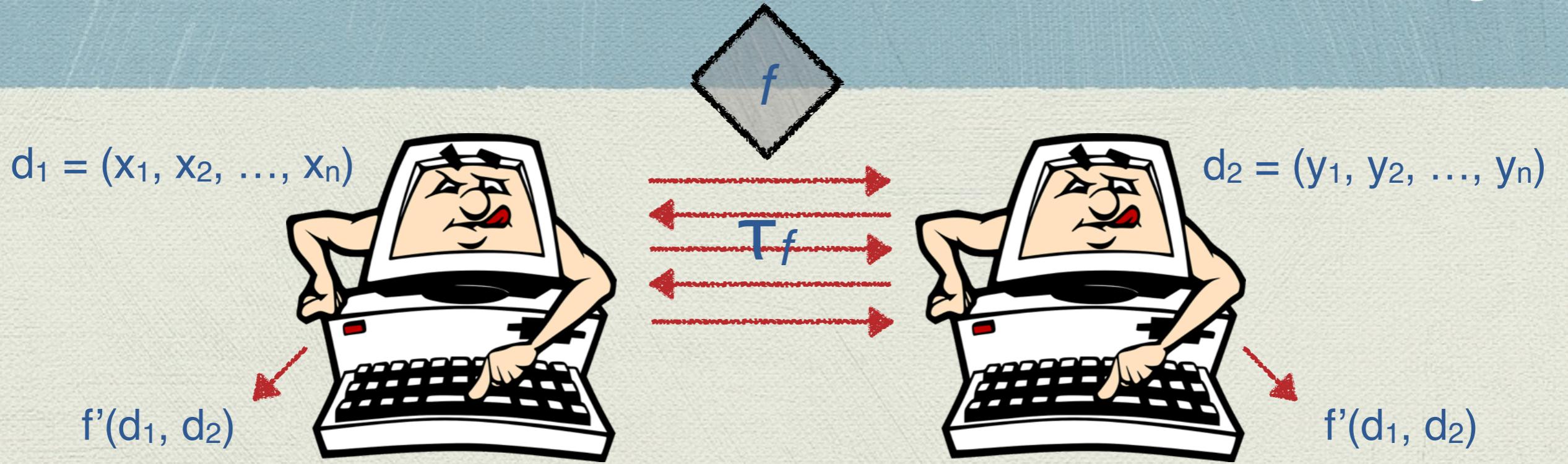
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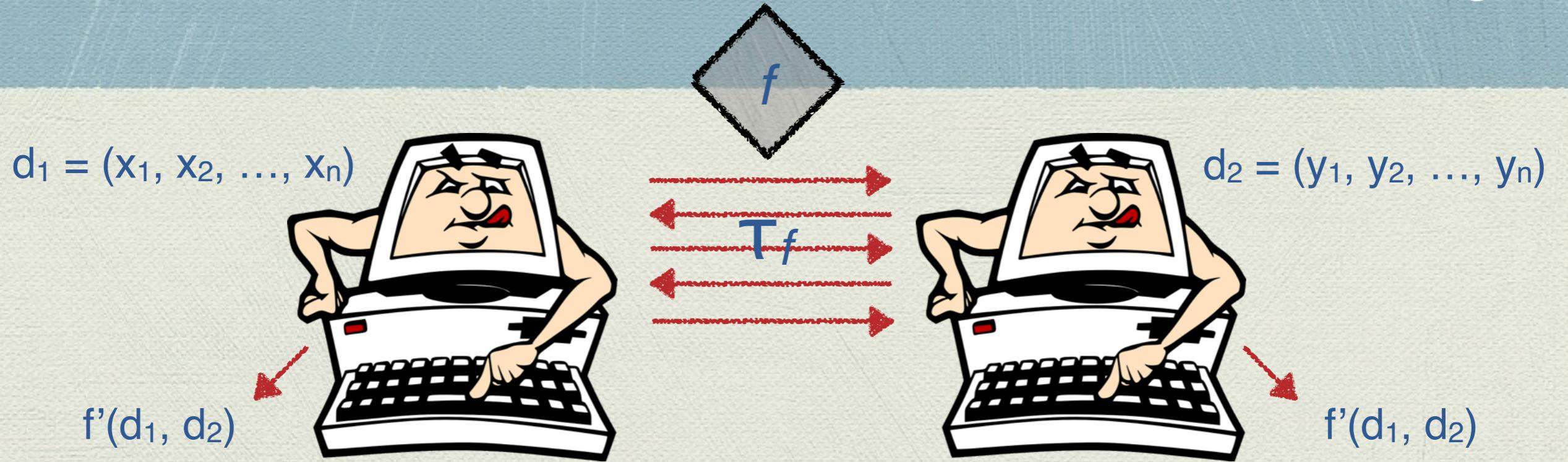
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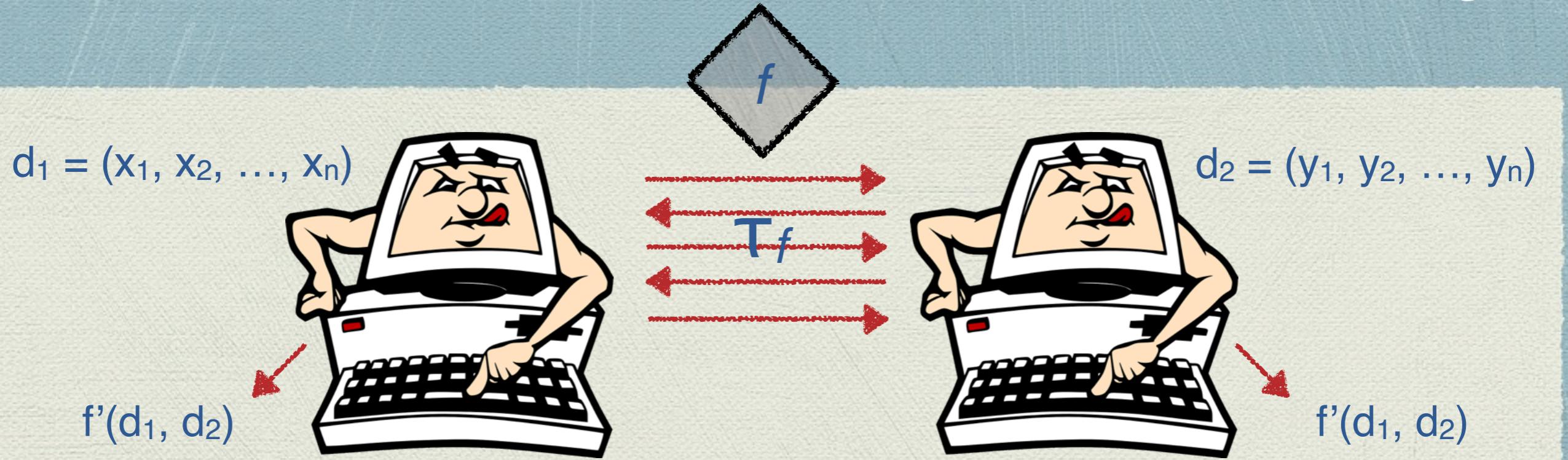


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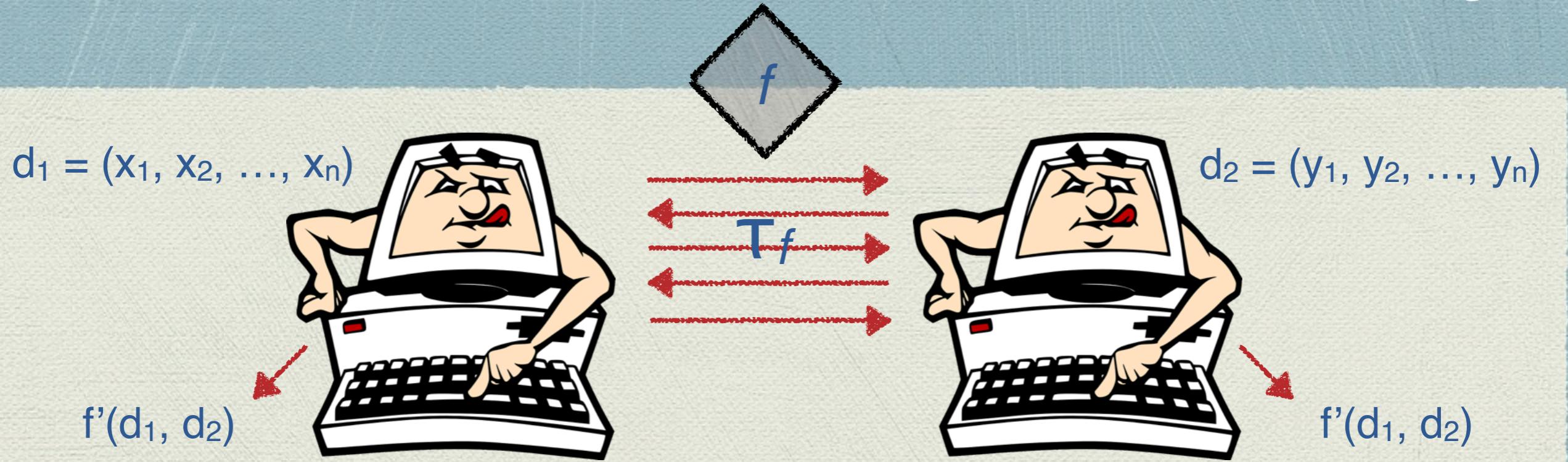
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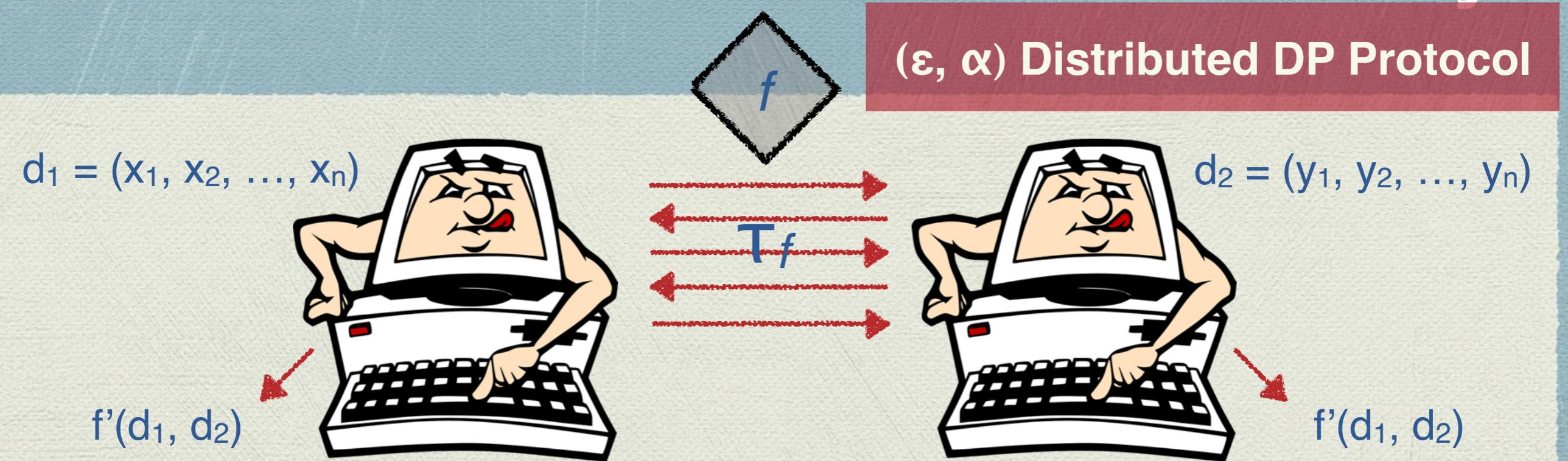
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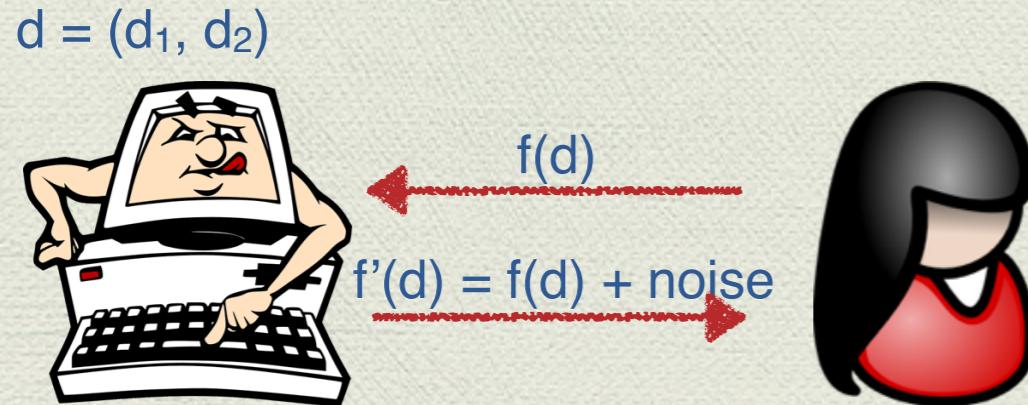
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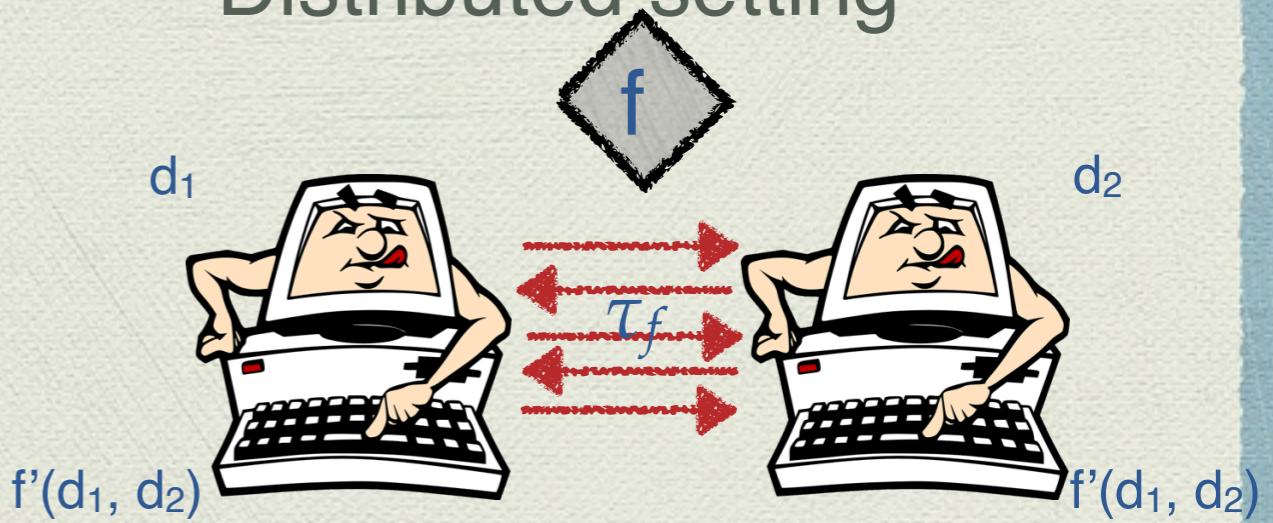
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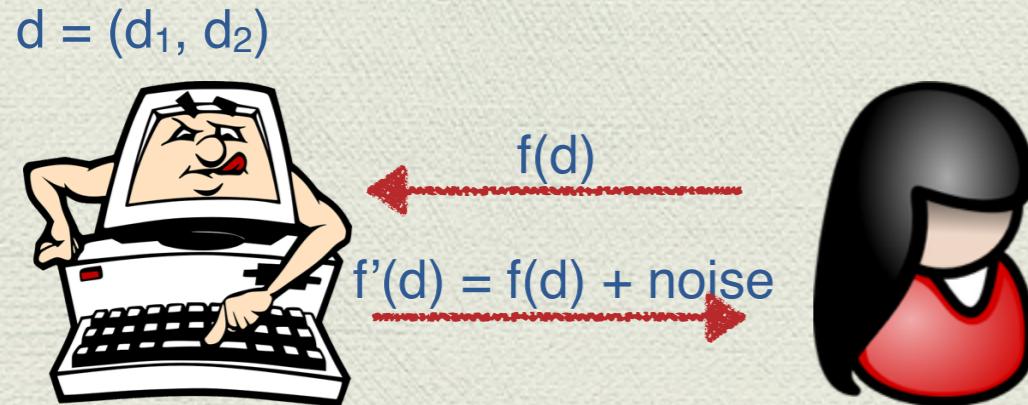
Distributed setting



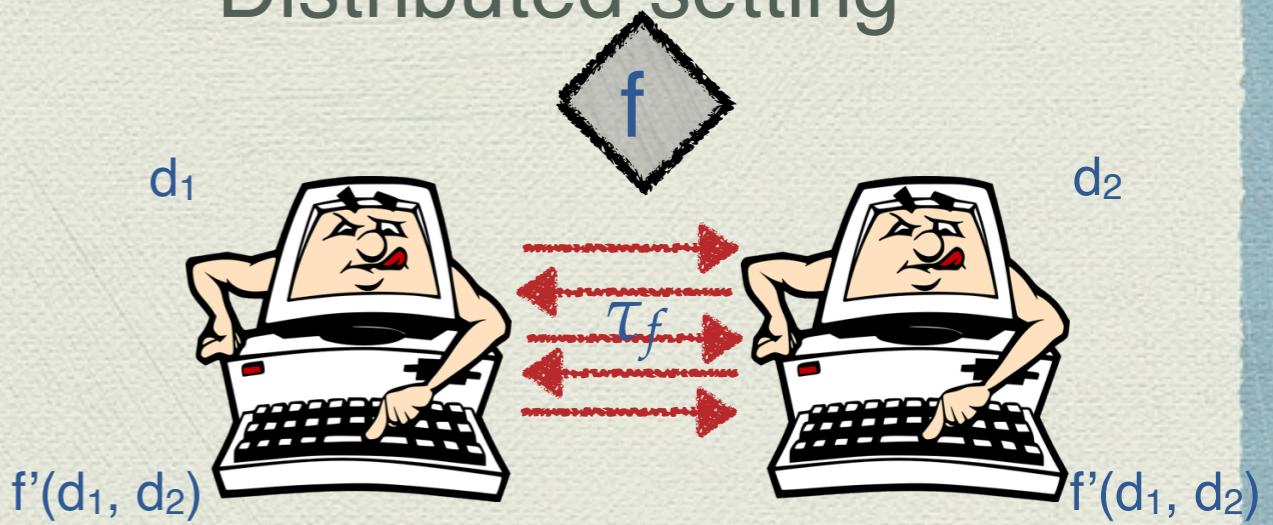
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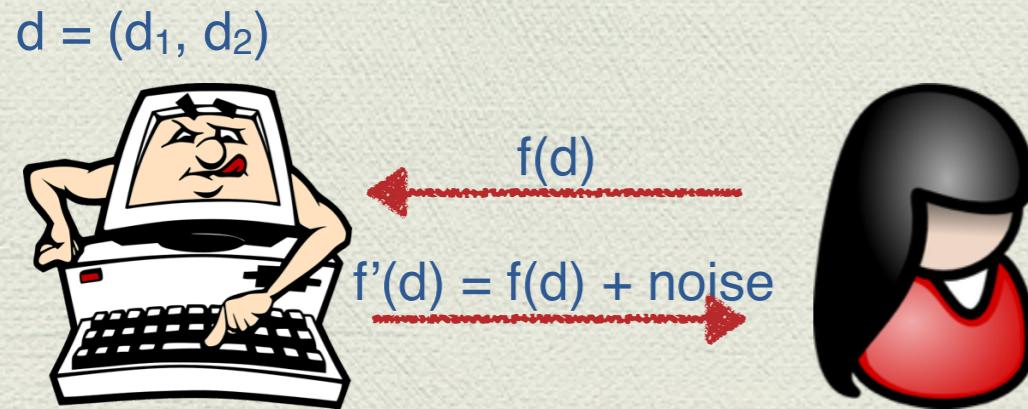


Privacy!

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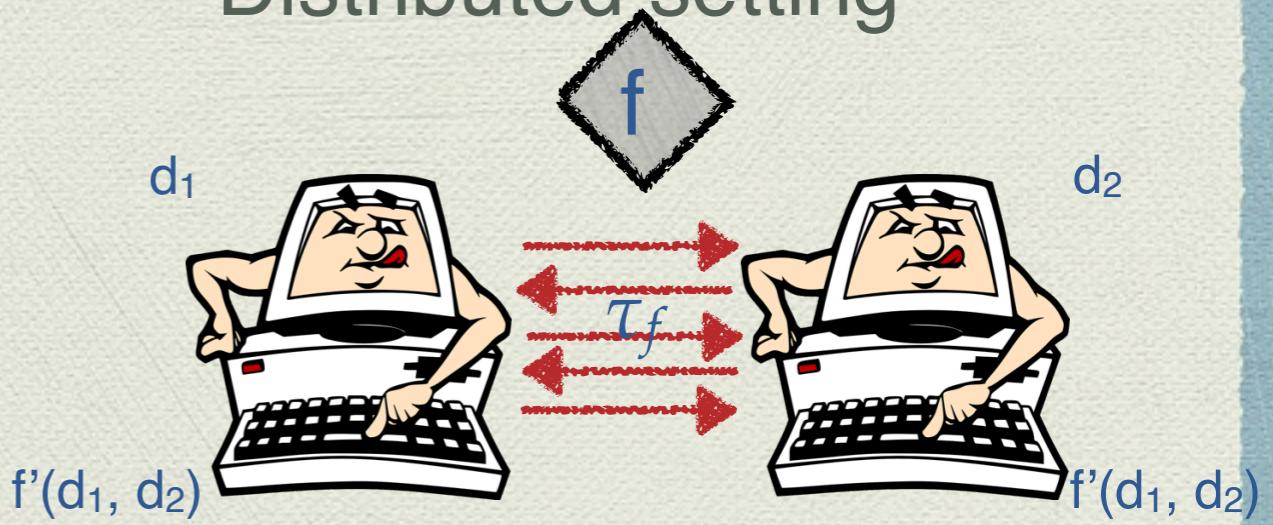
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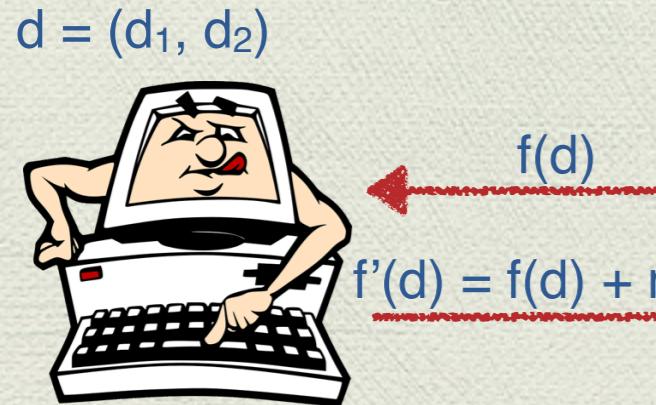


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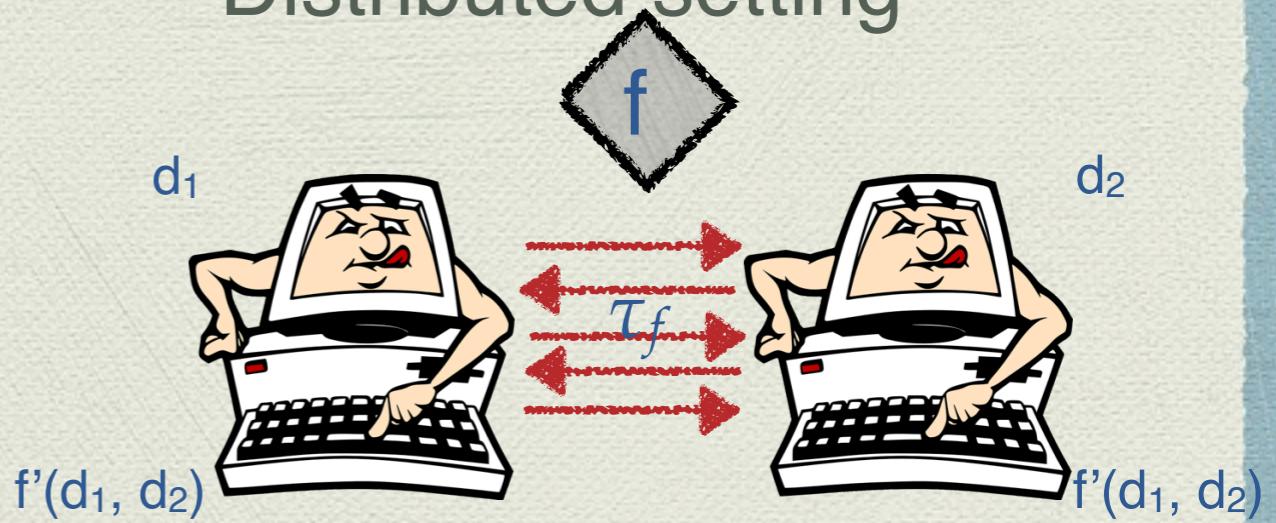
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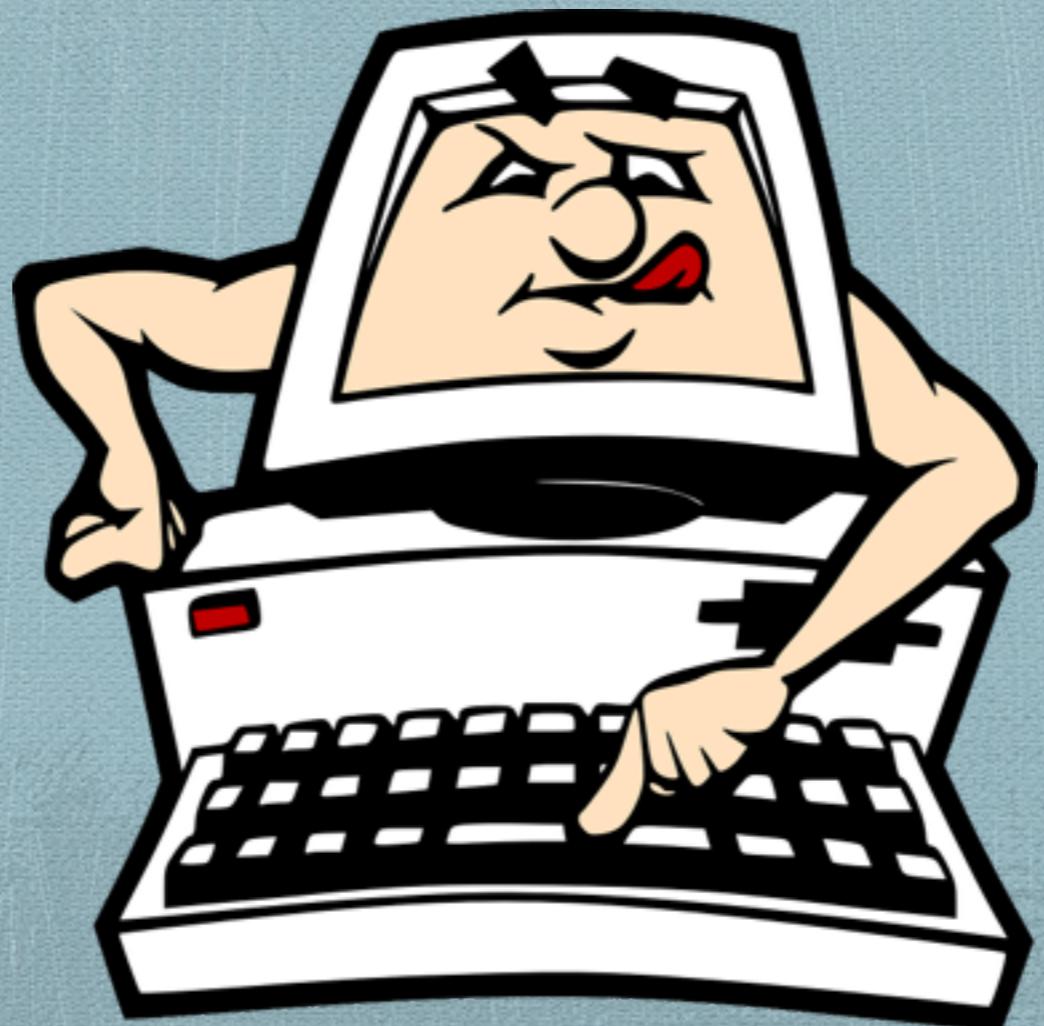
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# Problem Statement

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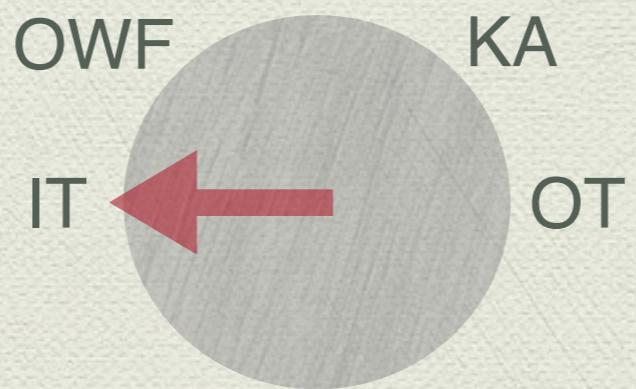
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No accuracy  
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# A Natural Question

Minimal assumption



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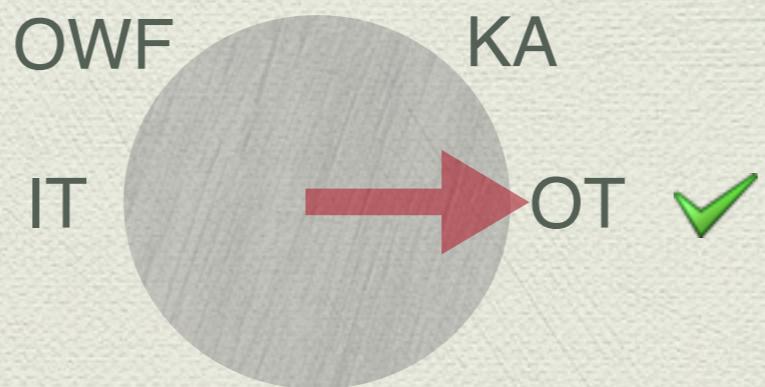
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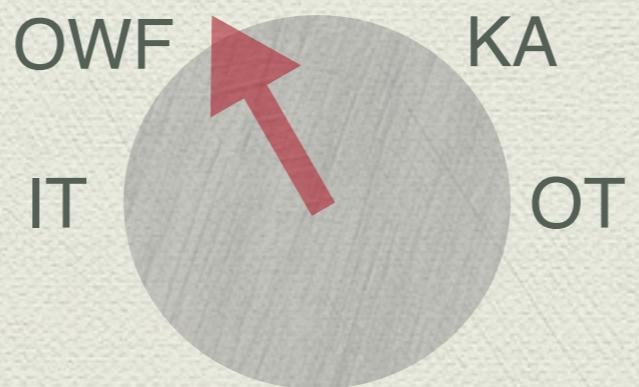
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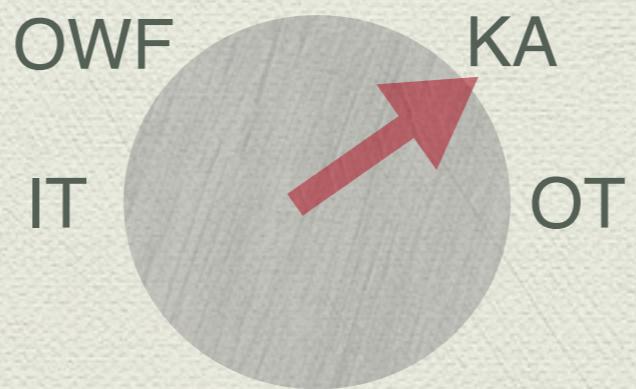
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# Main Theorem

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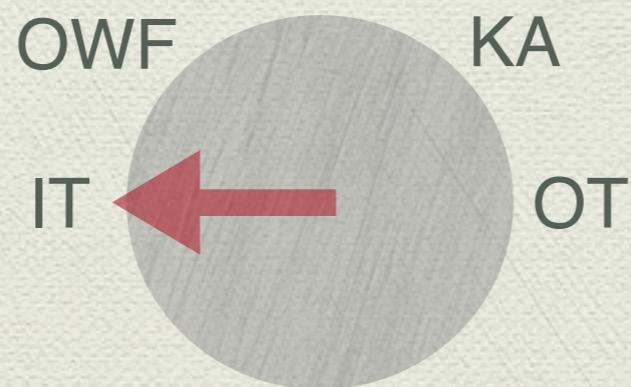
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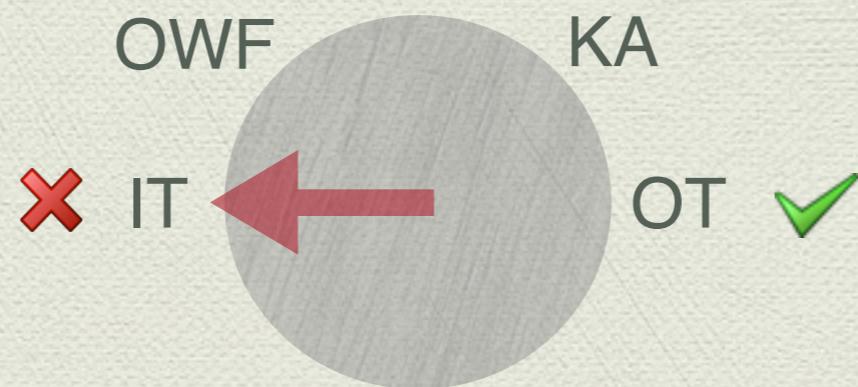
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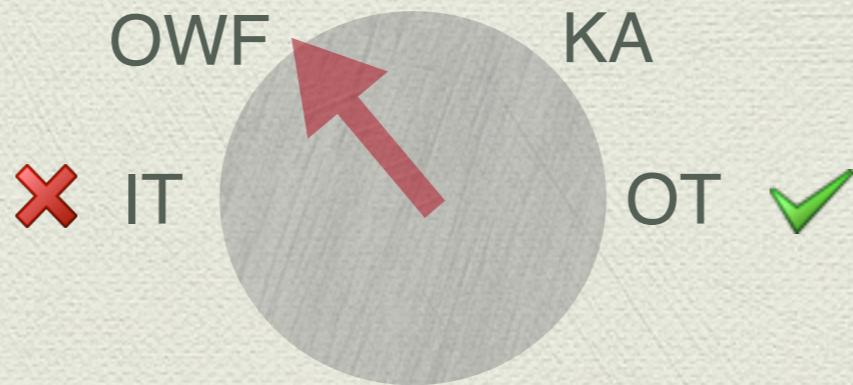
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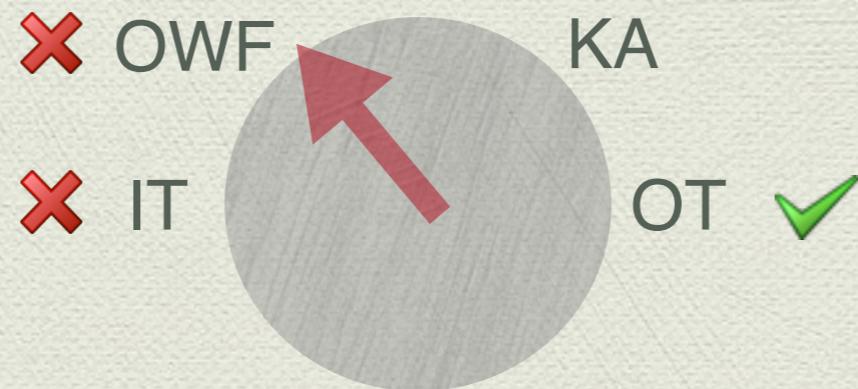
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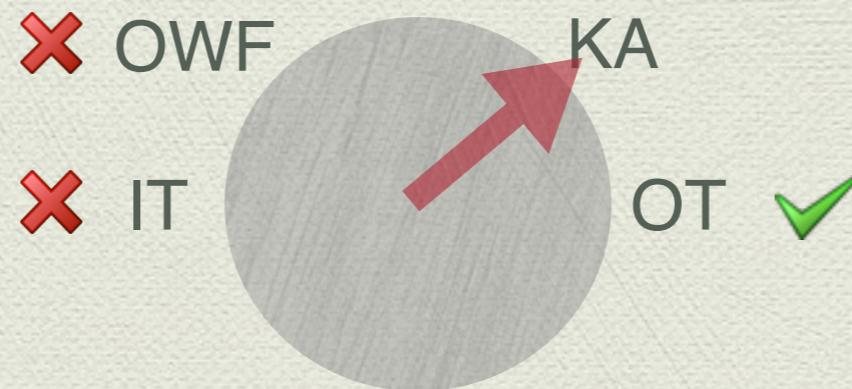
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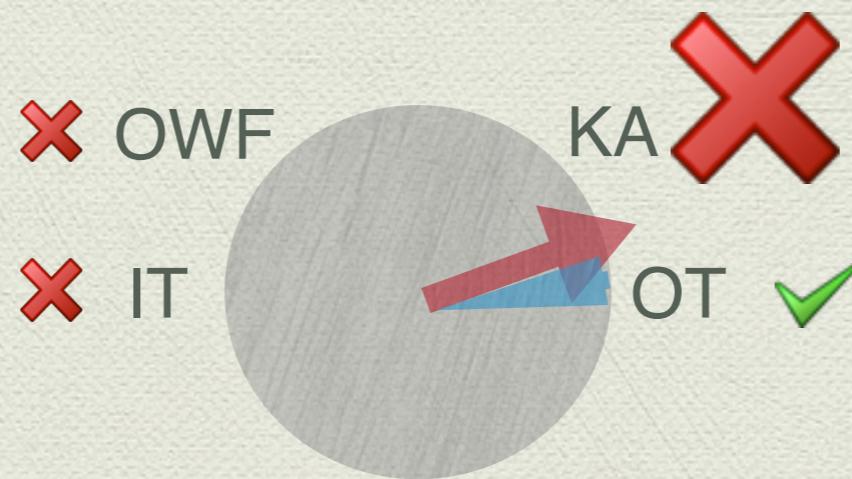
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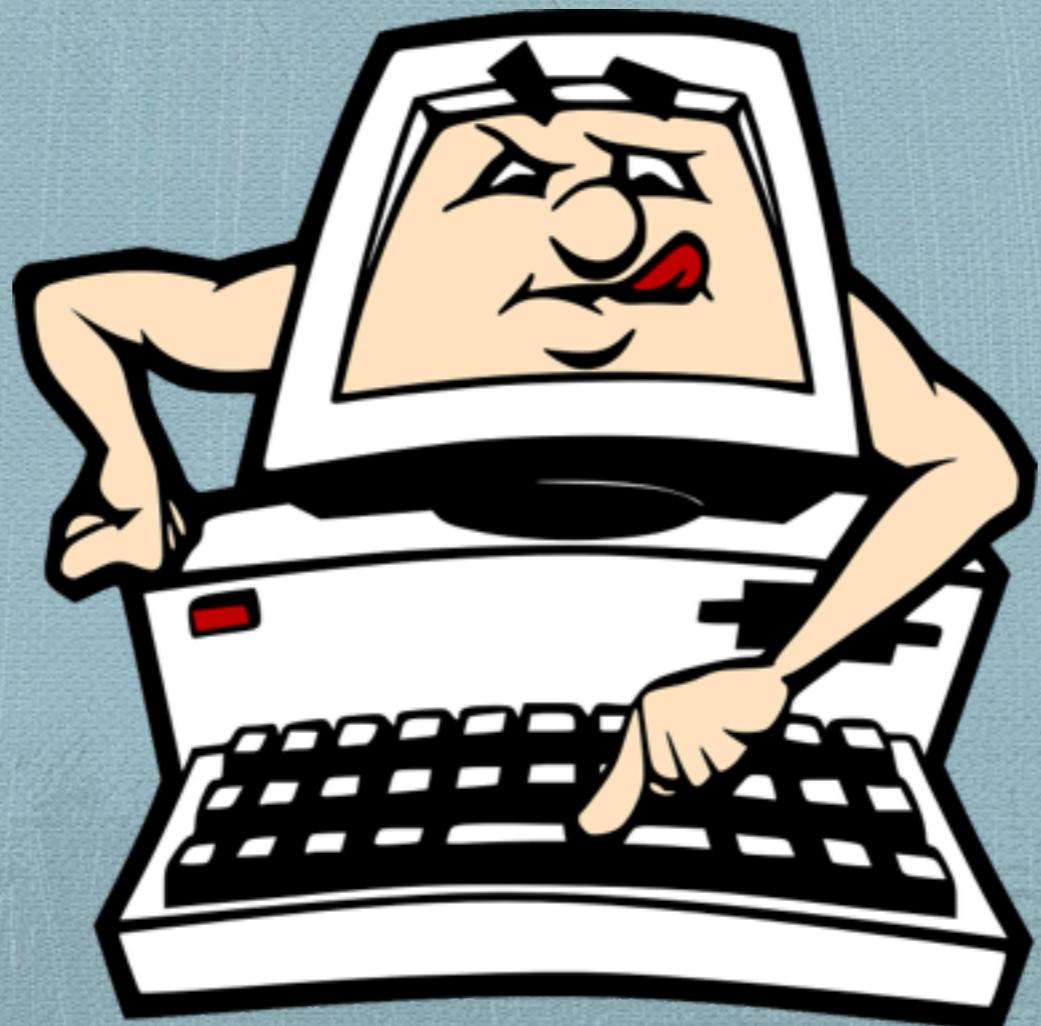
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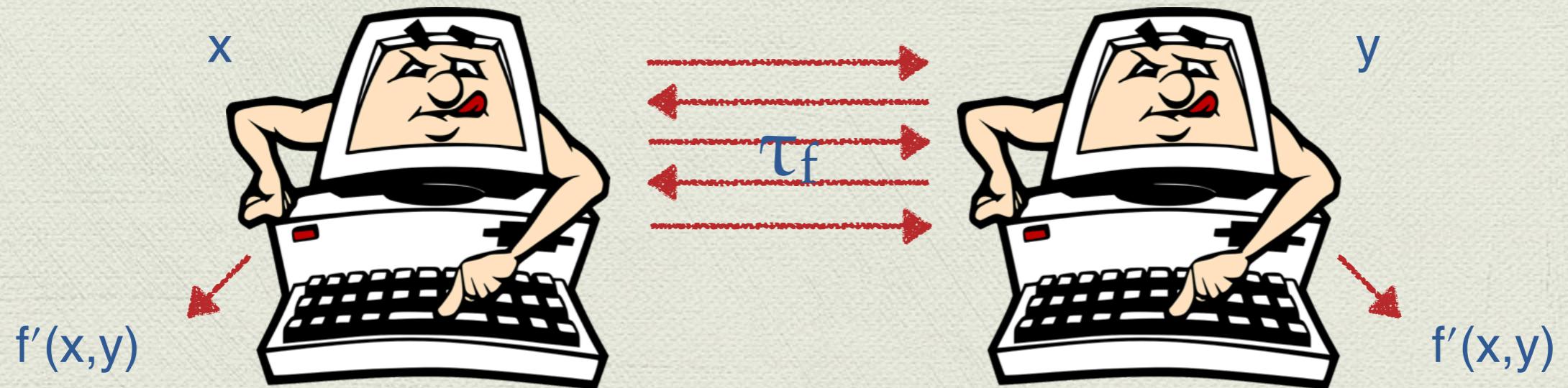
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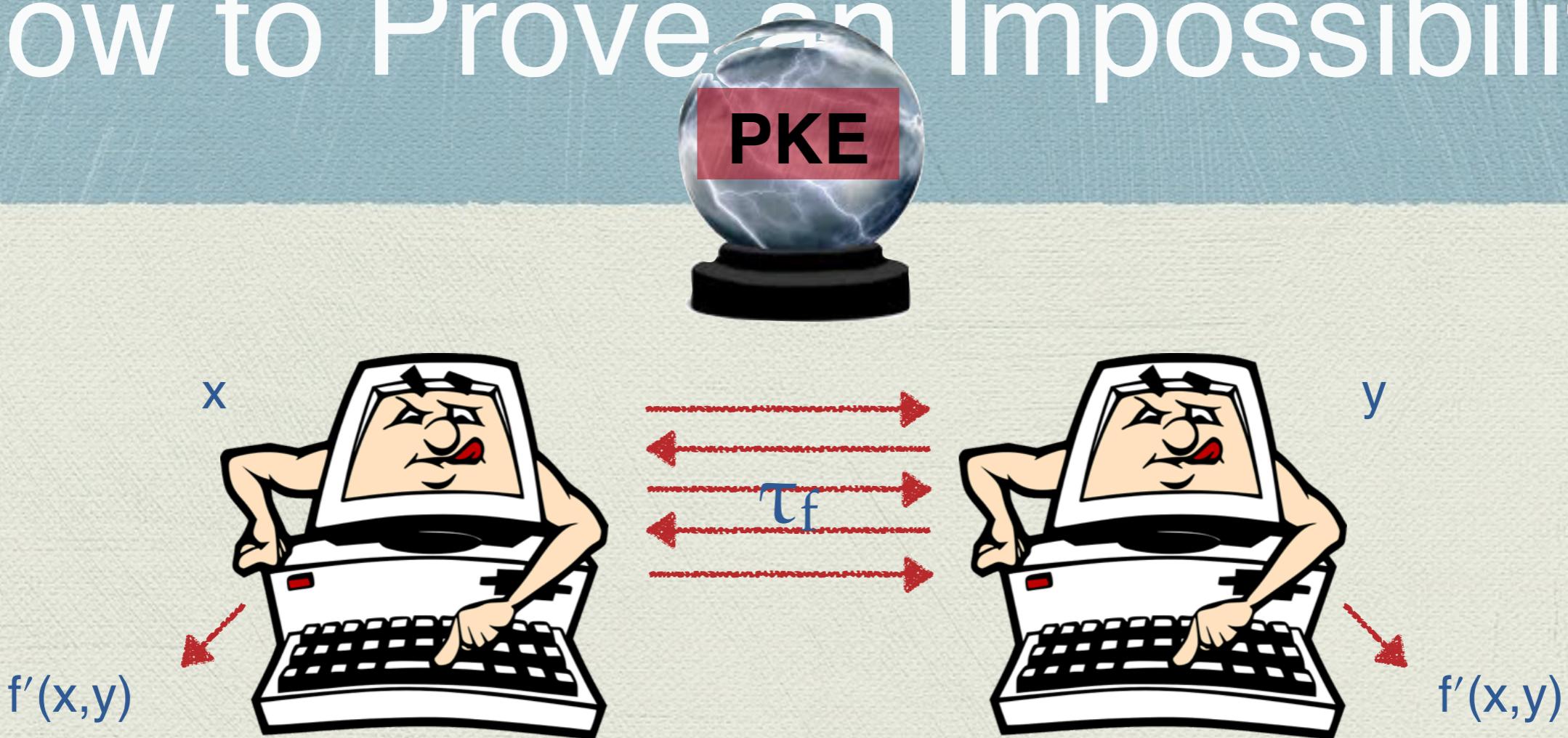
# Proving the Theorem

# How to Prove an Impossibility

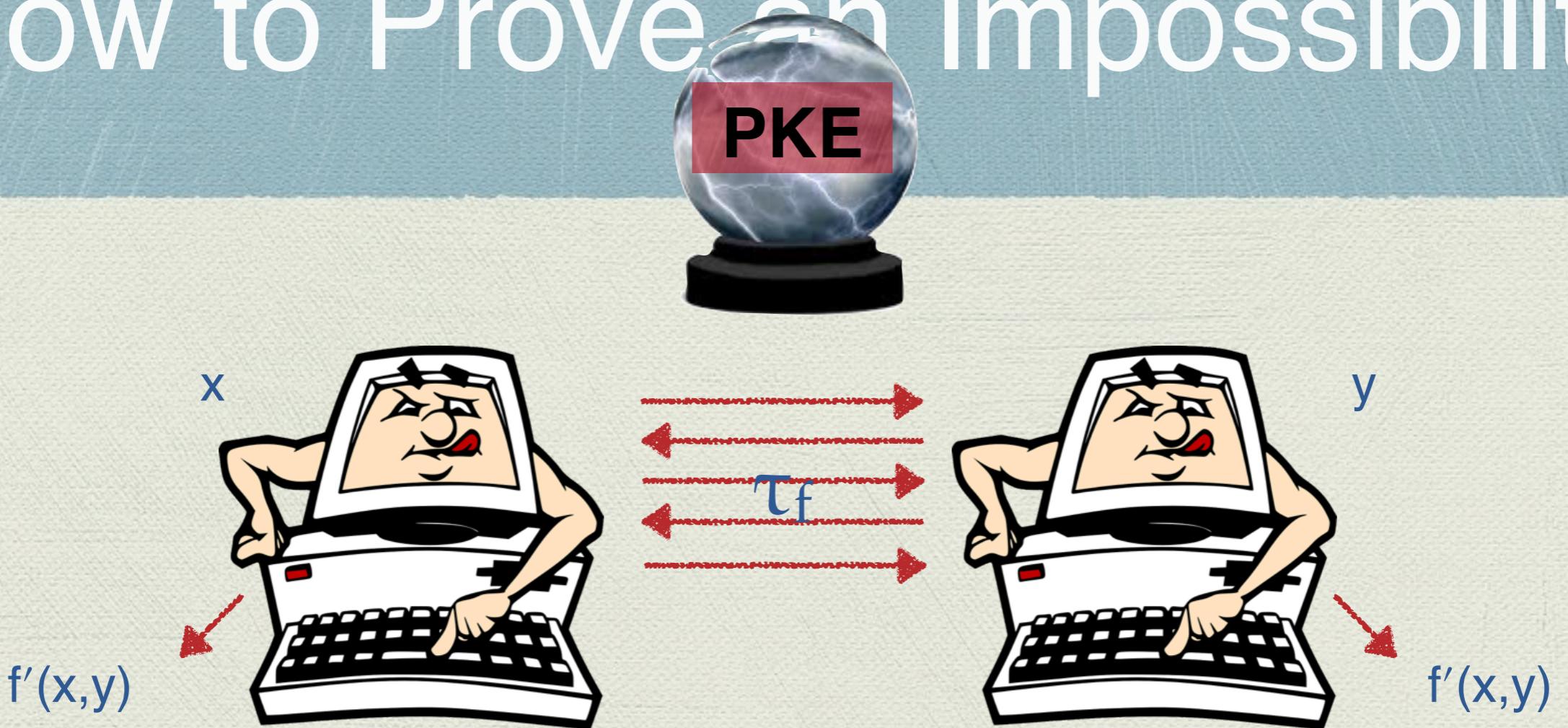
# How to Prove an Impossibility



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# How to Prove an Impossibility



PKE oracle allows key agreement but  
useless for optimally accurate distributed DP.

# How to Prove an impossibility?

- ◆ Black-box separation techniques [**Impagliazzo-Rudich '89, Barak-Mahmood '09**]
- ◆ Information-theoretic impossibility in PKE oracle world
- ◆ Use [**Reingold-Trevisan-Vadhan '04**] to convert oracle impossibility into a separation

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- ◆ All two-party non-trivial **Boolean** functions
  - ◆ Accuracy.  $\alpha = \min_{x,y} (\Pr[f'(x,y) = f(x,y)])$
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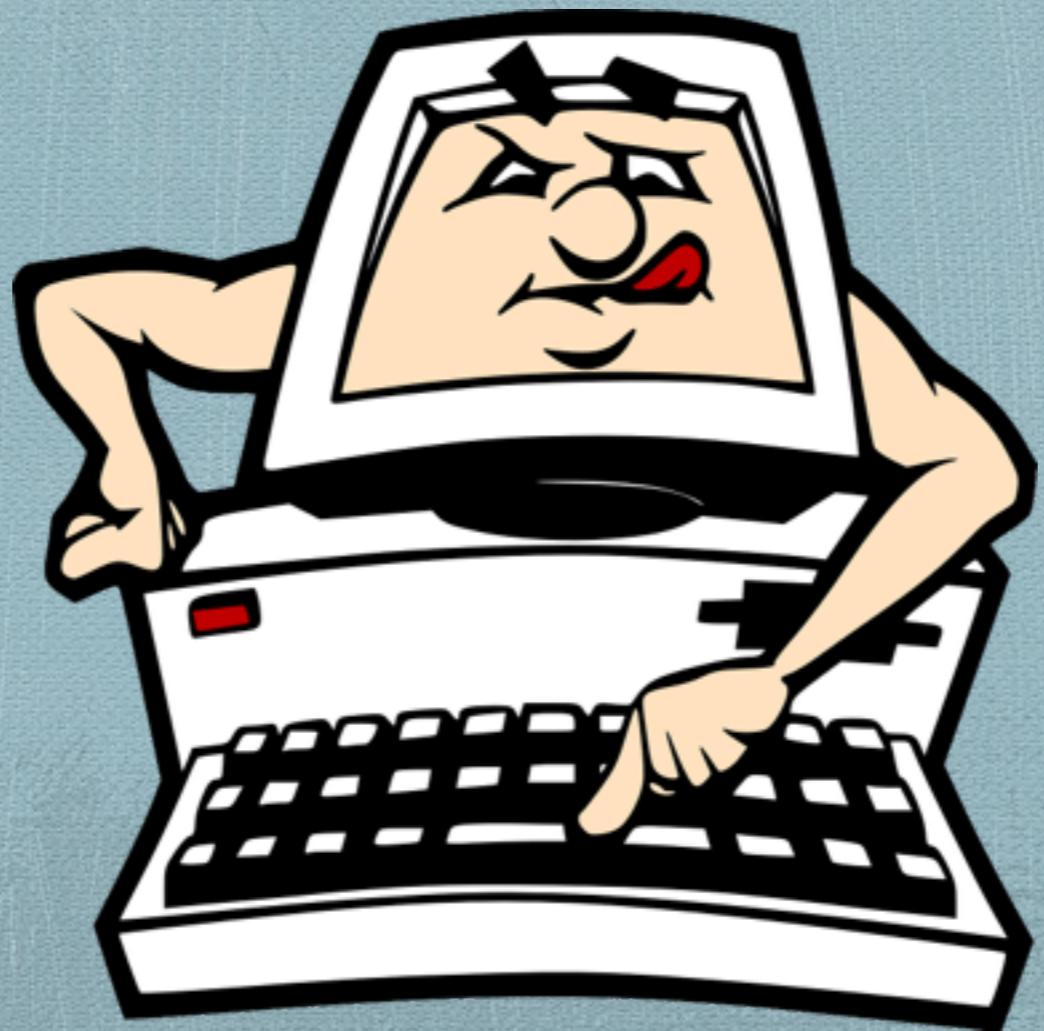
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- ◆ Consider representative **AND** and **XOR**
- ◆ Maximal achievable **distributed information-theoretic** accuracy [GMPS13]
  - ◆ **AND.**  $\alpha_{IT,AND,\varepsilon}^{(\text{dist})} = \lambda(\lambda^2 + \lambda + 2)/(\lambda+1)^3$ , for  $\lambda = \exp(\varepsilon)$ .
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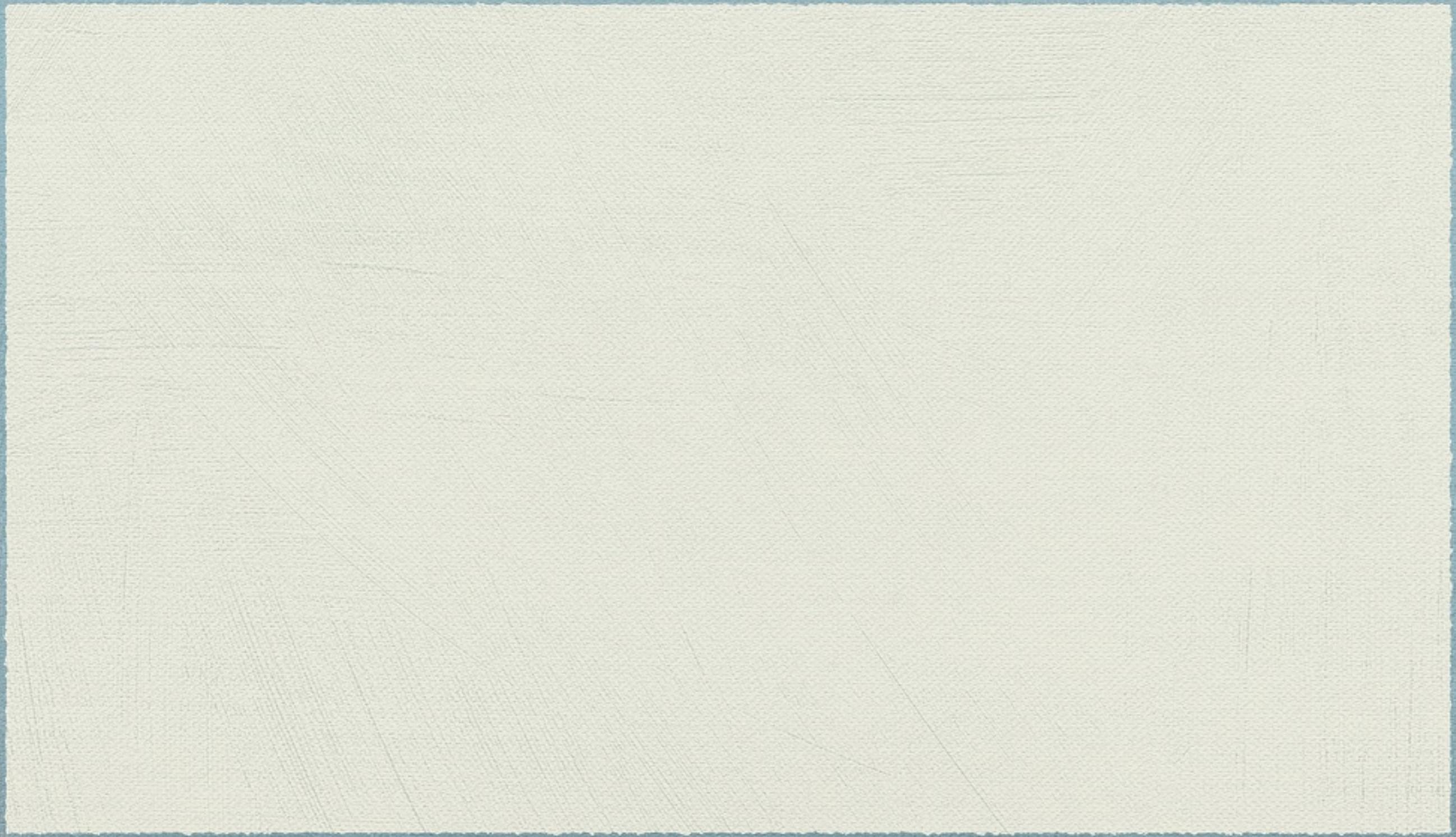
# In the PKE Oracle World

- ◆ We will show that maximal achievable distributed accuracy in **PKE oracle world**
- ◆ **AND.**  $\alpha_{\text{PKE}, \text{AND}, \varepsilon}^{(\text{dist})} \approx \lambda(\lambda^2 + \lambda + 2)/(\lambda+1)^3$ , for  $\lambda = \exp(\varepsilon)$ .
- ◆ **XOR.**  $\alpha_{\text{PKE}, \text{XOR}, \varepsilon}^{(\text{dist})} \approx (\lambda^2 + 1)/(\lambda+1)^2$ , for  $\lambda = \exp(\varepsilon)$ .



# Oracle Separation

# Information Theoretic Plain Model



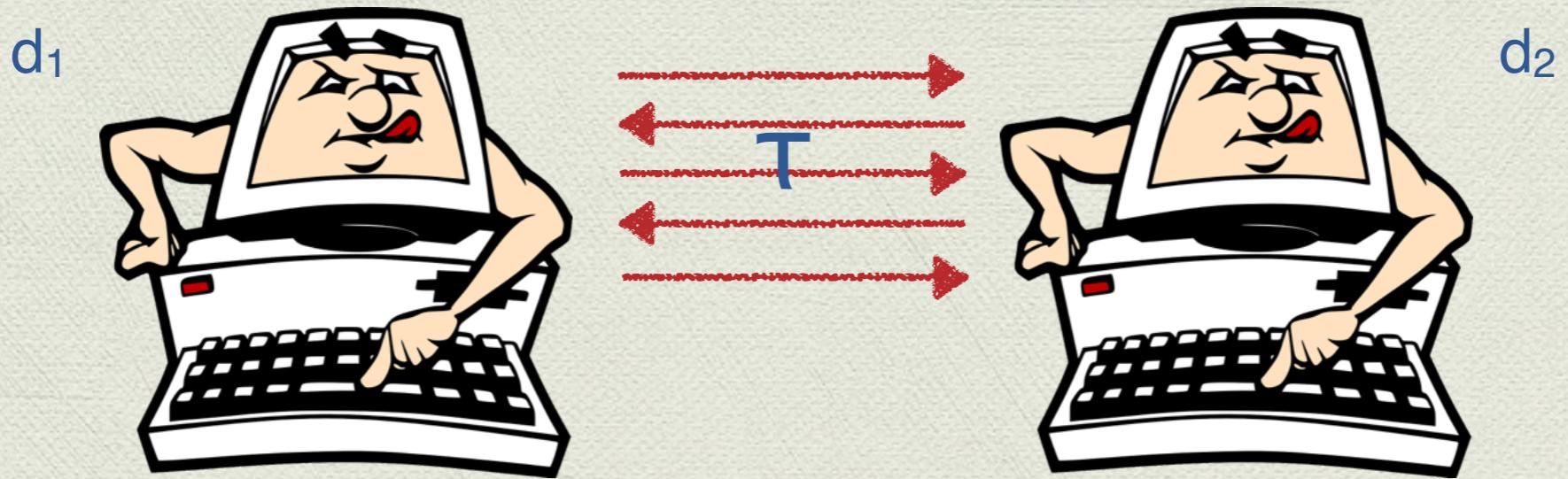
# Information Theoretic Plain Model



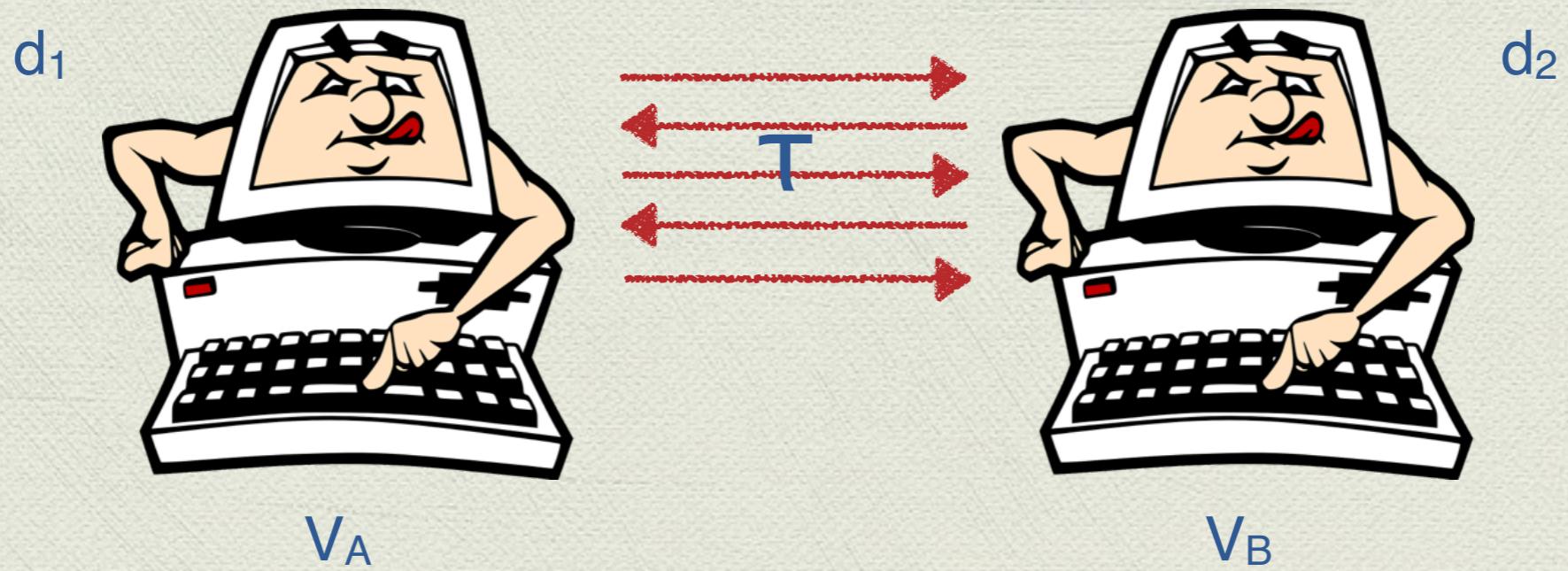
# Information Theoretic Plain Model



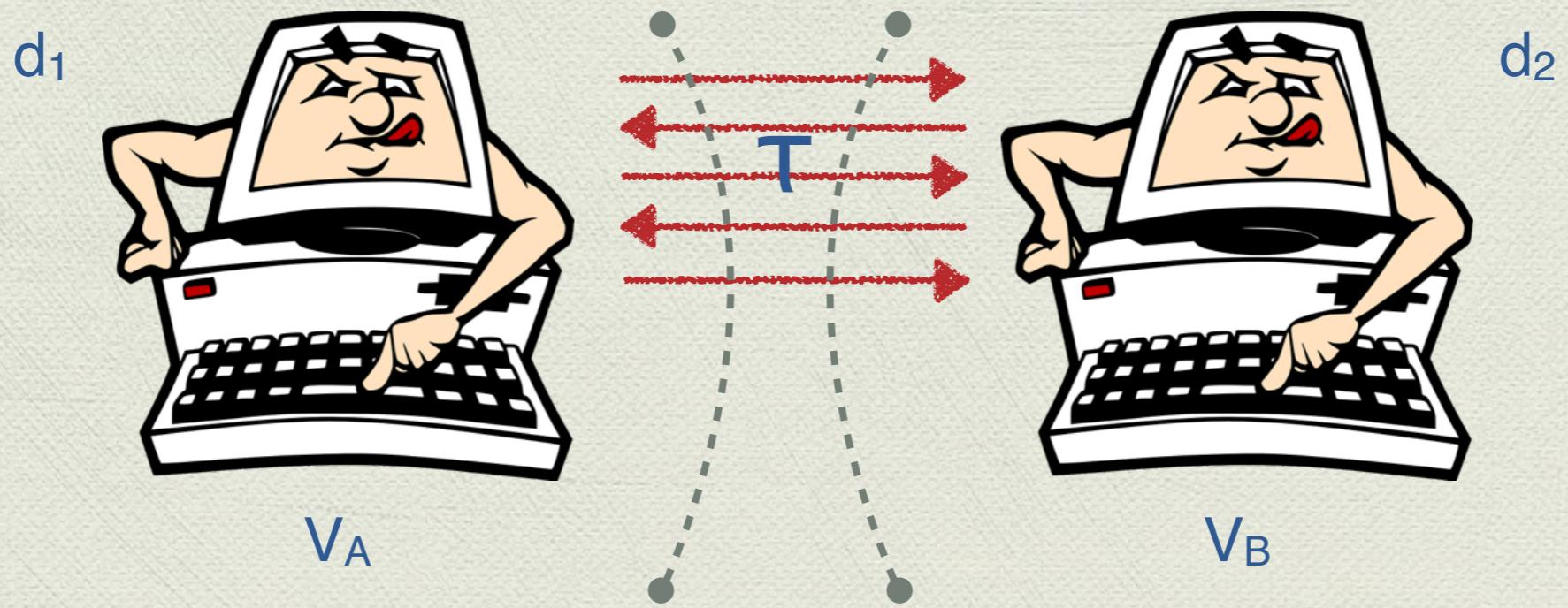
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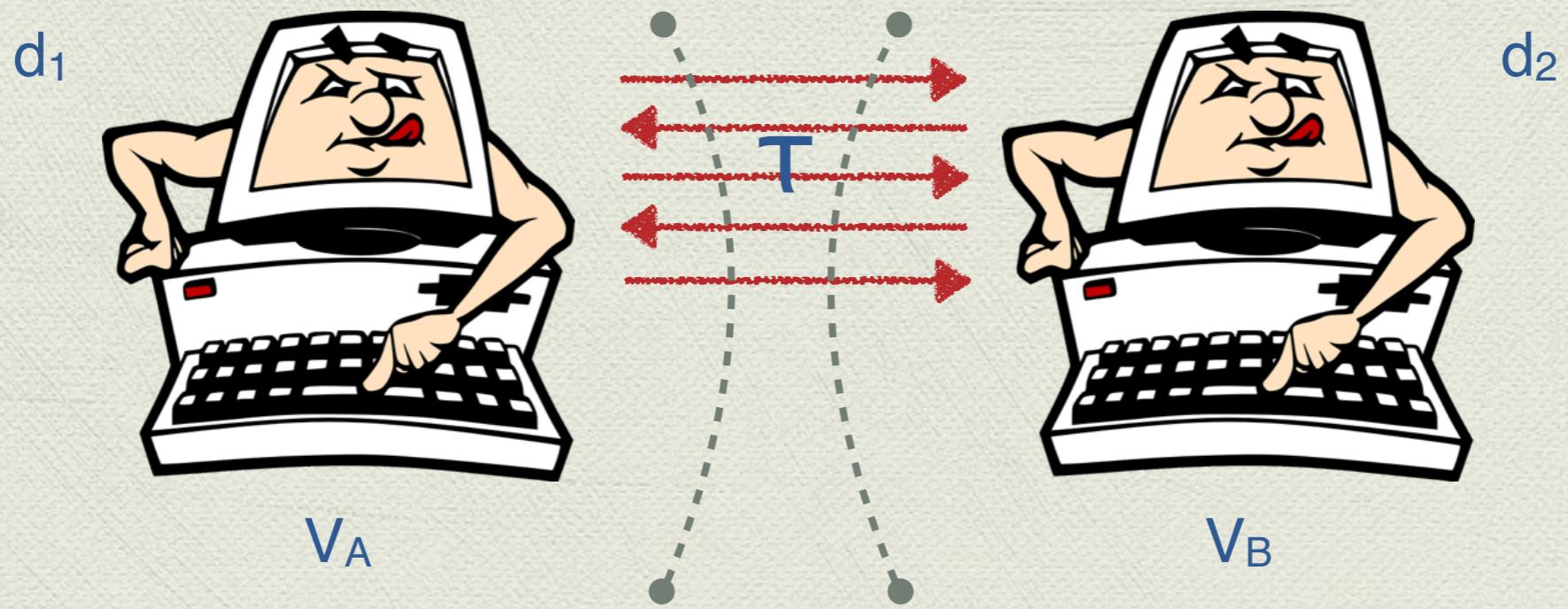


# Information Theoretic Plain Model



- ◆ Independent views.  
 $(V_A \times V_B | \tau, d_1, d_2) = (V_A | \tau, d_1) \times (V_B | \tau, d_2)$

# Information Theoretic Plain Model



- Independent views.

$$(V_A \times V_B | \tau, d_1, d_2) = (V_A | \tau, d_1) \times (V_B | \tau, d_2)$$

⇒ optimal accuracy cannot be achieved

[GMPS13]

# Information Theoretic PKE World

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# Information Theoretic PKE World

$d_1$



$d_2$



# Information Theoretic PKE World



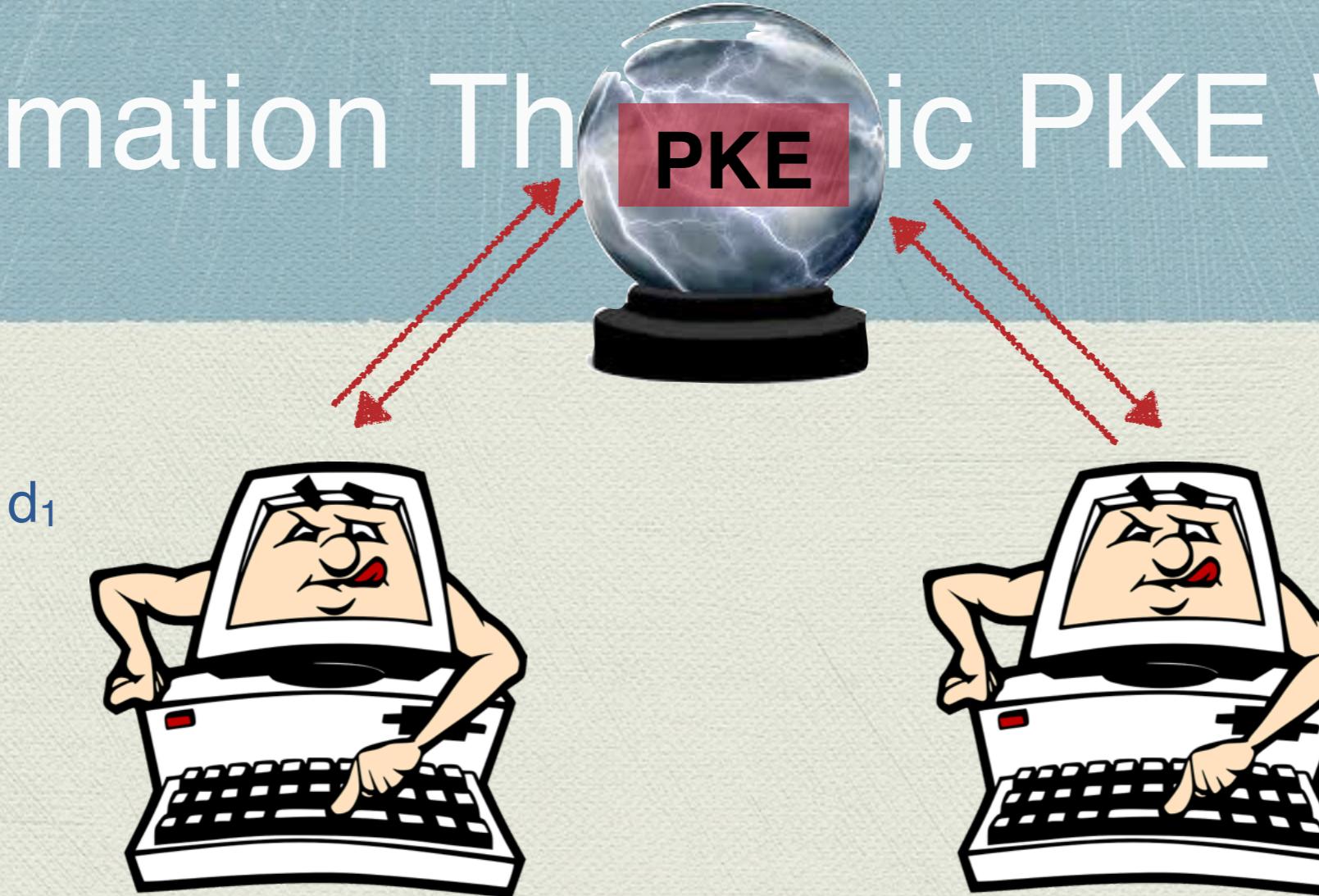
$d_1$



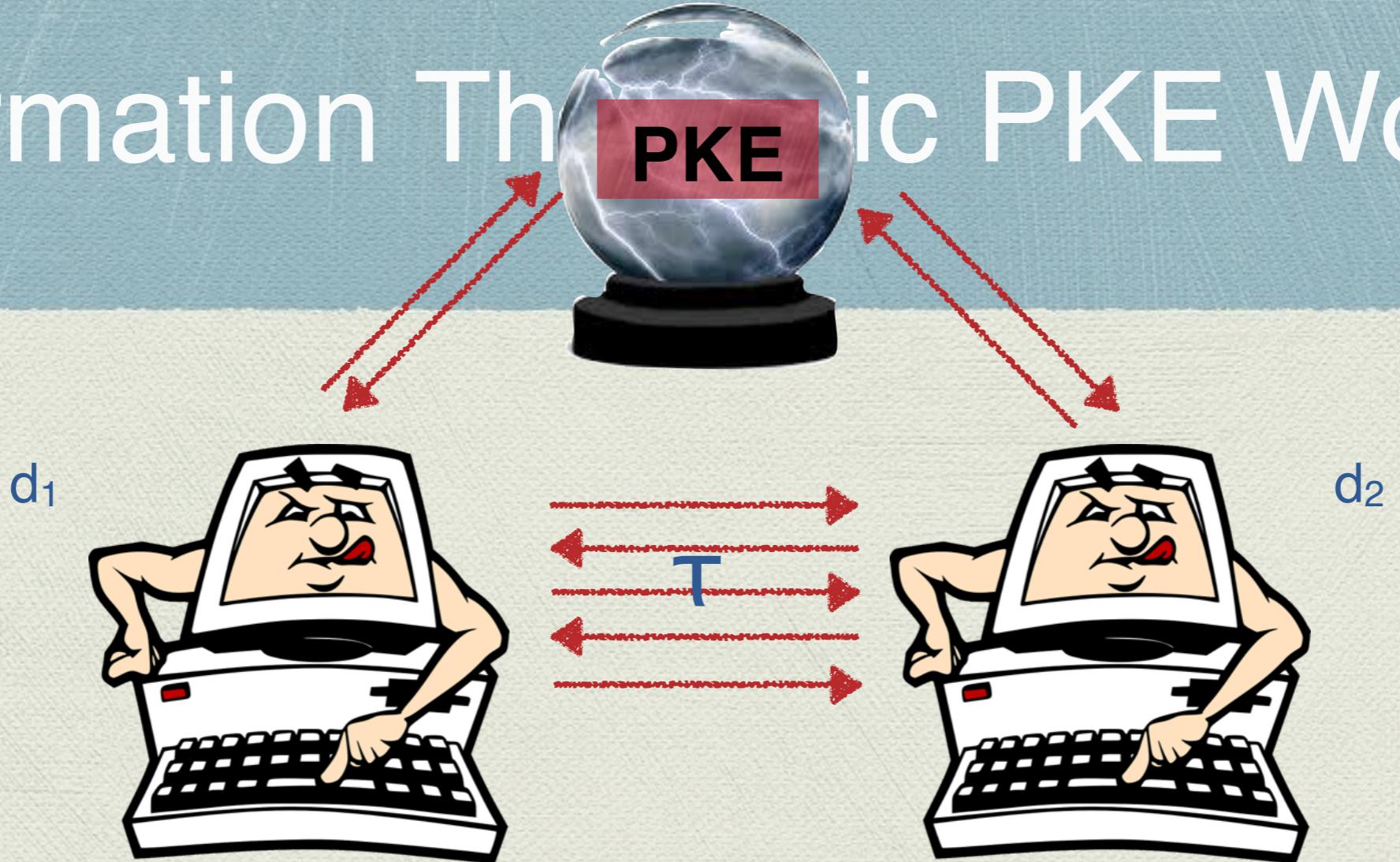
$d_2$



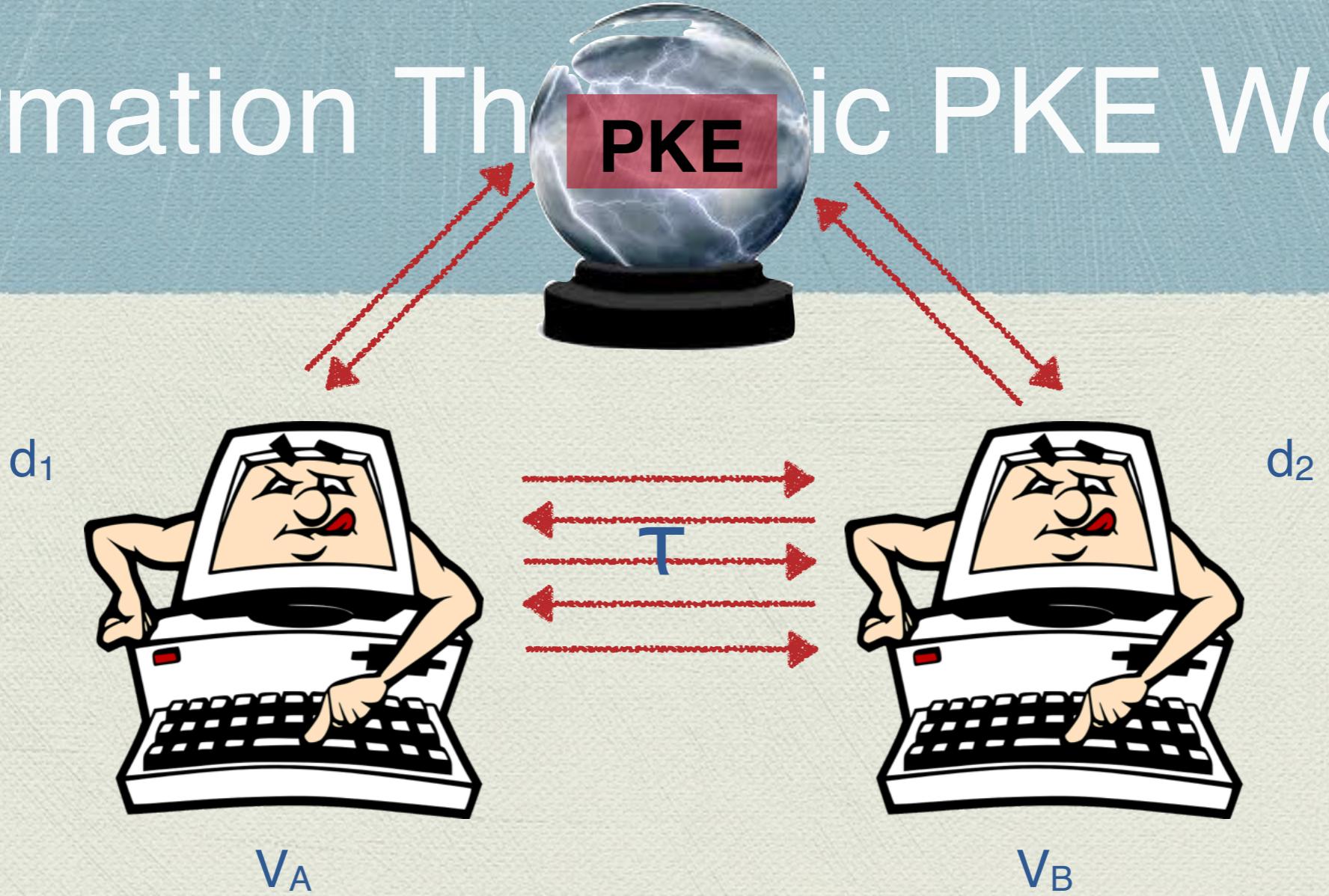
# Information Theoretic PKE World



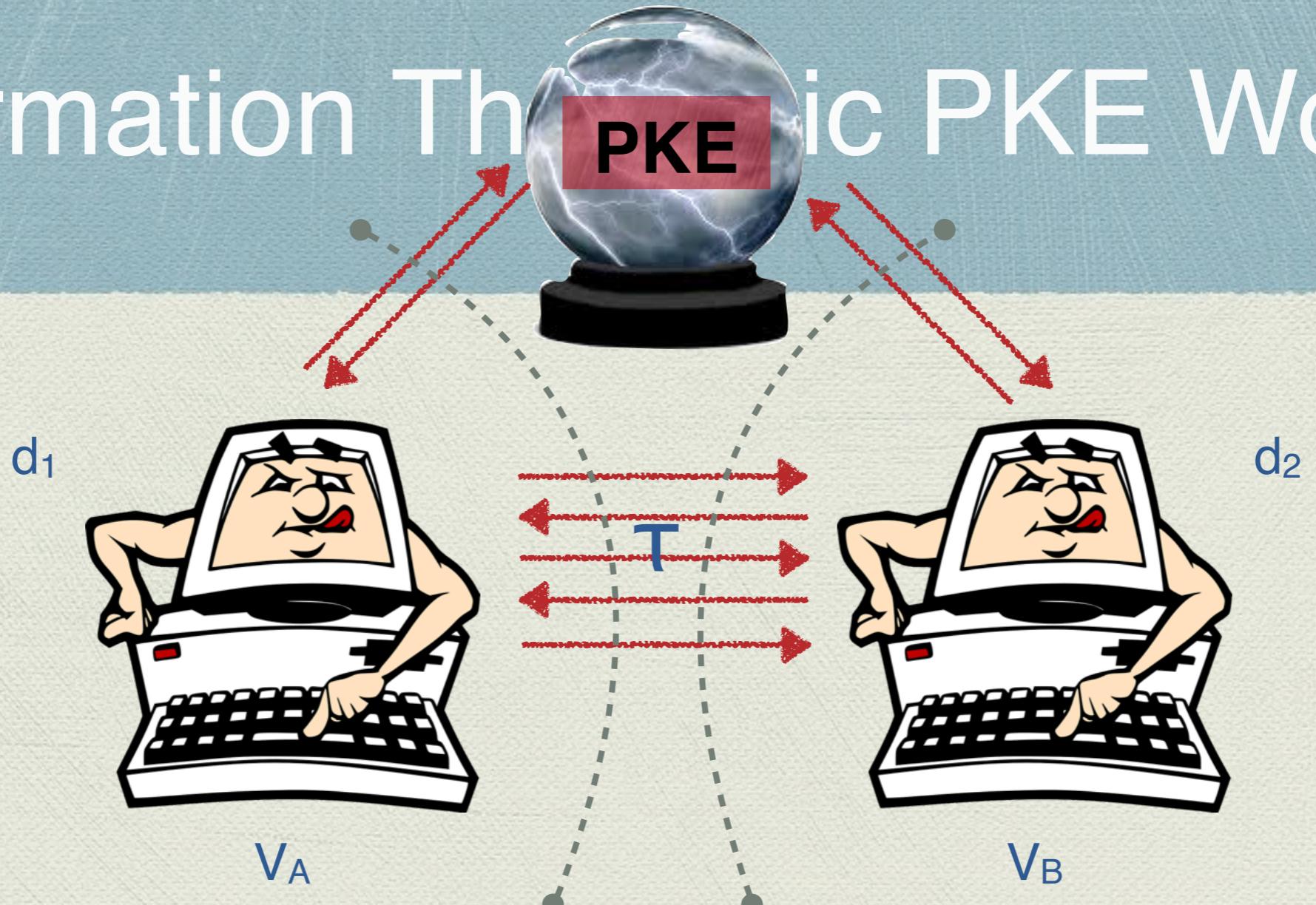
# Information Theory in the PKE World



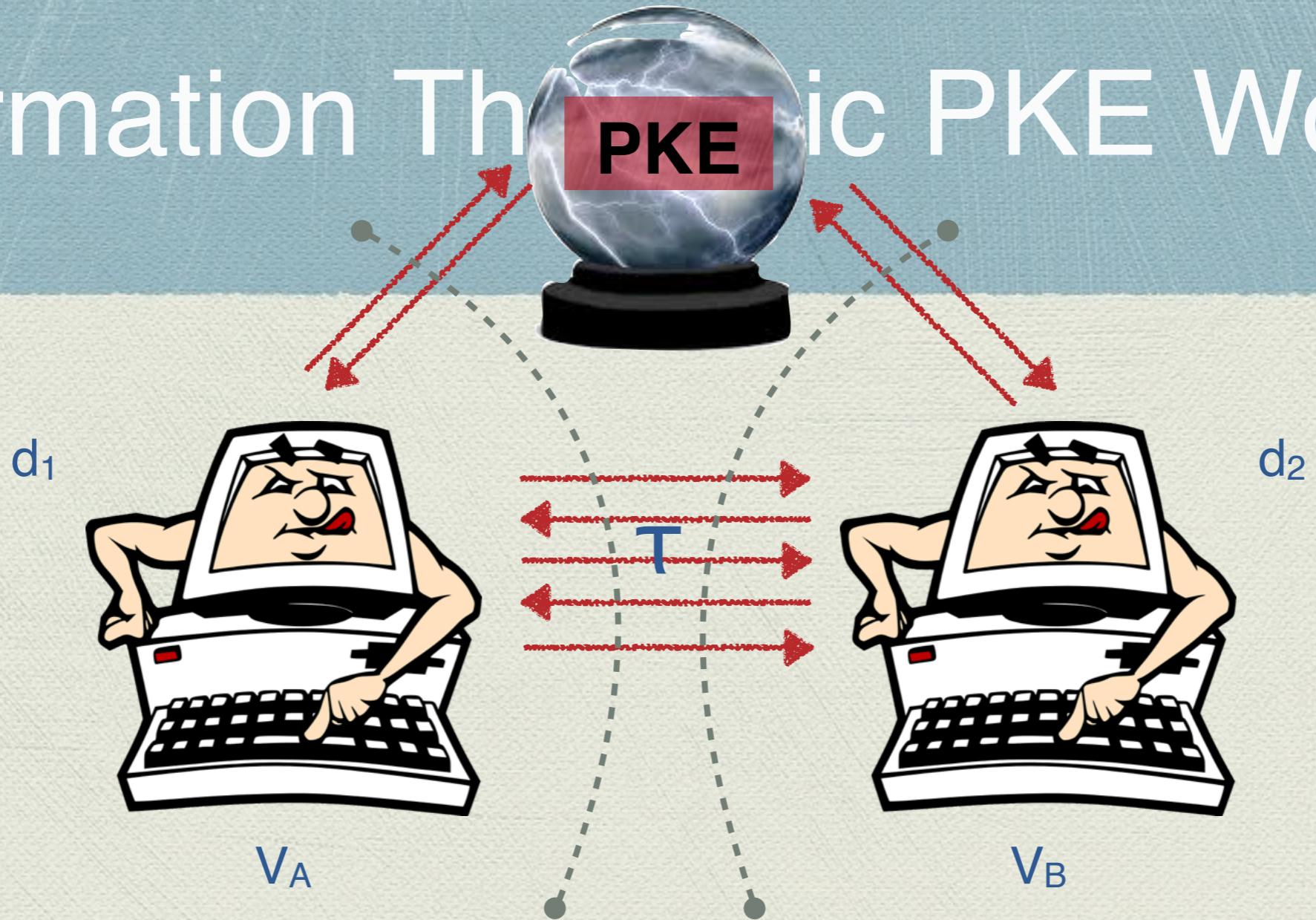
# Information Theory in PKE World



# Information Theory in the PKE World



# Information Theory in the PKE World



- ◆ Views no longer independent  
⇒ optimal accuracy could possibly be achieved

# PKE Oracle

# PKE Oracle

- **PKE = (Gen, Enc, Dec)**
- $\text{Gen } (\text{sk}) \rightarrow \text{pk}$ . Length-tripling Random Oracle
- $\text{Enc } ^{(\text{pk})}(\text{m}) \rightarrow \text{c}$ . (Collection of keyed) Length-tripling Random Oracles
- $\text{Dec } ^{(\text{sk})}(\text{c}) \rightarrow \text{m}$ . (Smallest)  $\text{m}$ :  $\text{pk}=\text{Gen}(\text{sk})$ ,  $\text{c}=\text{Enc}^{(\text{pk})}(\text{m})$

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# PKE Oracle

- **PKE = (Gen, Enc, Dec) + (Test<sub>1</sub>, Test<sub>2</sub>)**
- **Gen** ( $\text{sk}$ )  $\rightarrow \text{pk}$ . Length-tripling Random Oracle
- **Enc**  $(\text{pk})(\text{m}) \rightarrow \text{c}$ . (Collection of keyed) Length-tripling Random Oracles
- **Dec**  $(\text{sk})(\text{c}) \rightarrow \text{m}$ . (Smallest)  $\text{m}$ :  $\text{pk} = \text{Gen}(\text{sk})$ ,  $\text{c} = \text{Enc}(\text{pk})(\text{m})$
- **Test<sub>1</sub>** ( $\text{pk}$ ) = 0/1. Whether there exists  $\text{sk}$  such that  $\text{Gen}(\text{sk}) = \text{pk}$
- **Test<sub>2</sub>**  $(\text{pk})(\text{c}) = 0/1$ . Whether there exists  $\text{m}$  such that  $\text{Test}^{(\text{pk})}(\text{m}) = \text{c}$

# PKE World

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- ◆ Compile out **Decryption Oracle** following  
[Mahmoody-Maji-Prabhakaran 2014, TCC]

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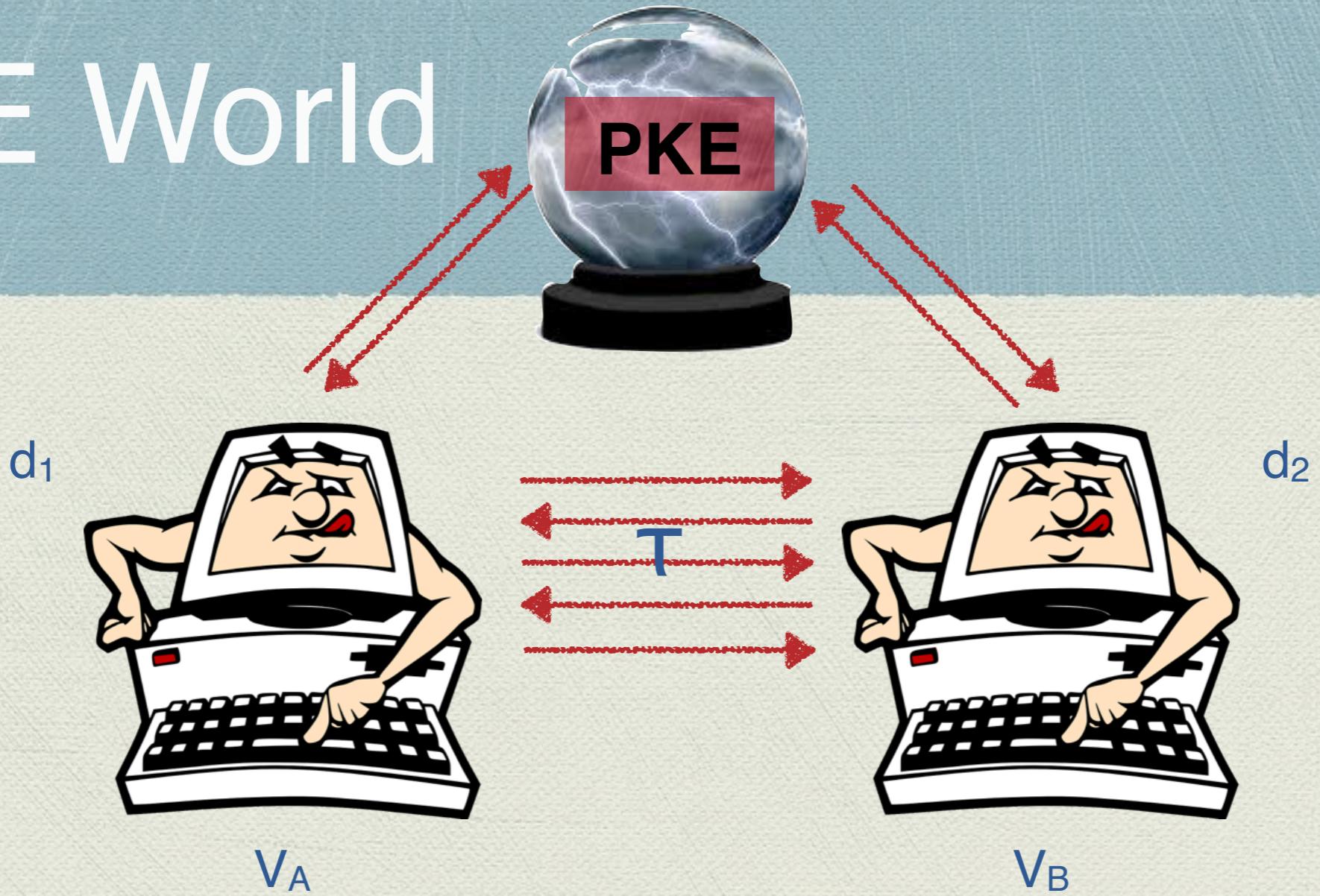
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- ◆ **(Gen, Enc, Test<sub>1</sub>, Test<sub>2</sub>)** remain

# PKE World

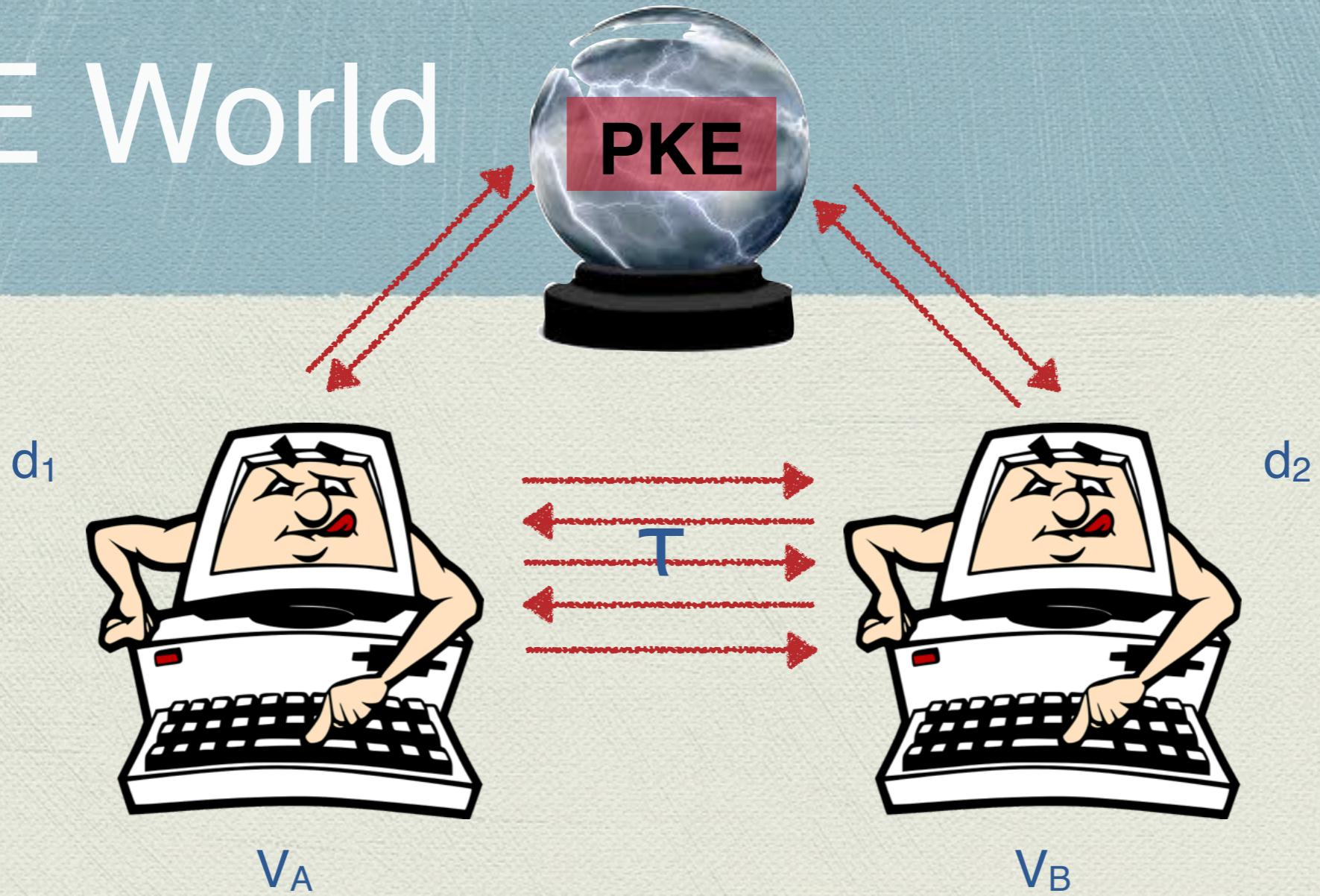
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- ◆ **(Gen, Enc, Test<sub>1</sub>, Test<sub>2</sub>)** remain
- ◆ Compiled protocol has slightly lower accuracy

# PKE World

# PKE World

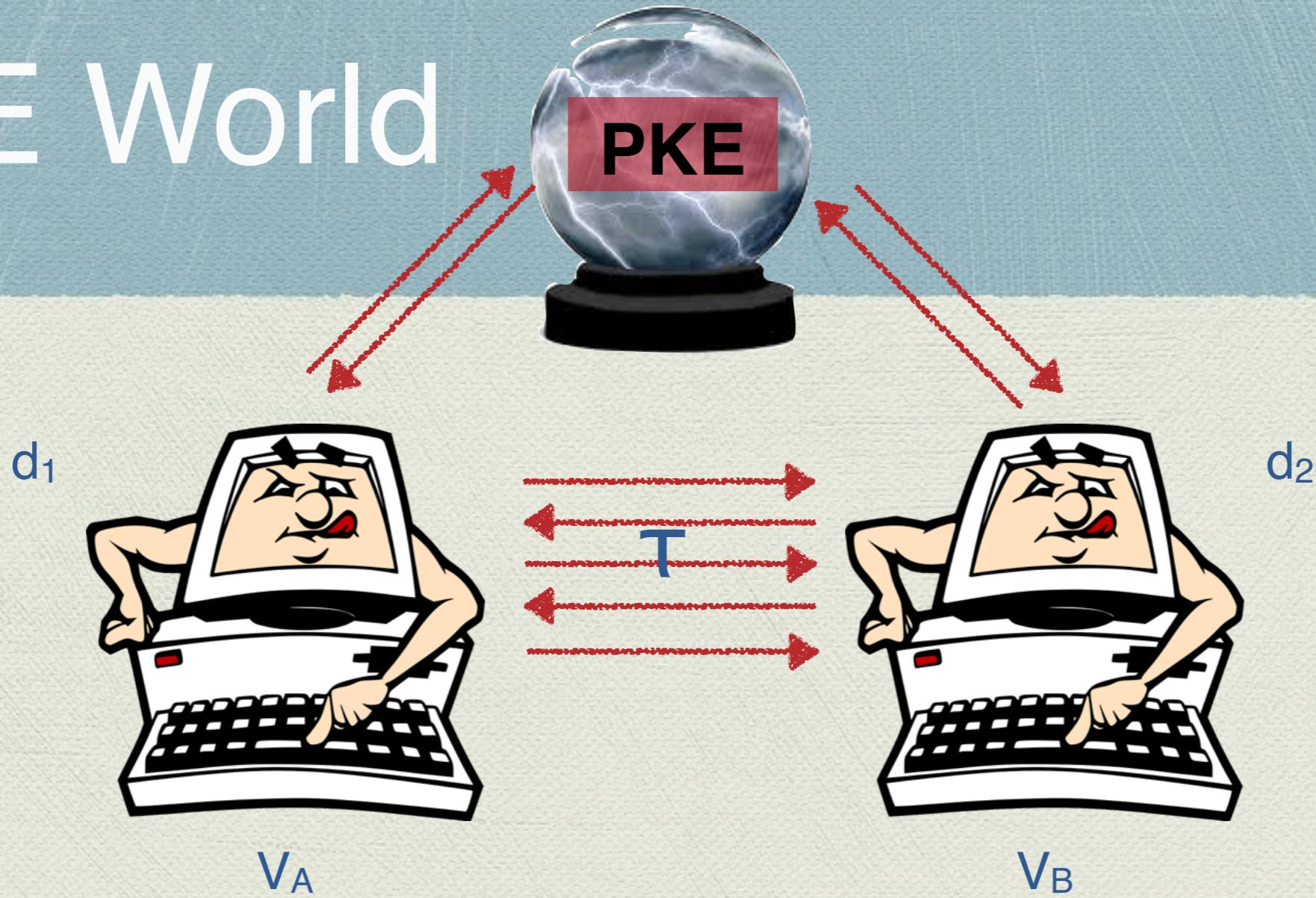


# PKE World



- ◆  $\forall (\varepsilon, \alpha)$  DP protocol in PKE World
- ⇒  $\exists (\varepsilon, \alpha^-)$  DP protocol in (PKE - Dec) World

# PKE World

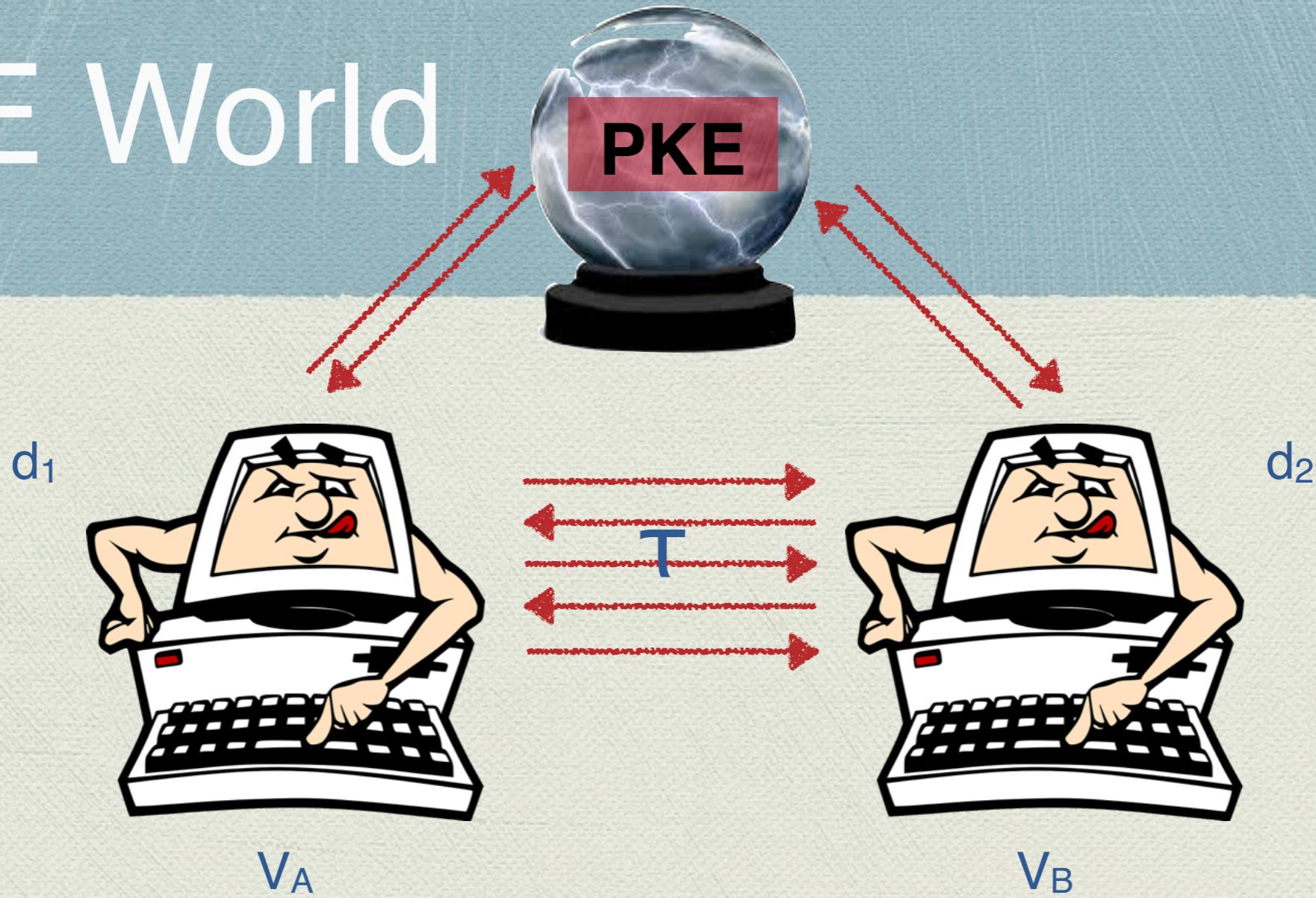


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[MMP14- TCC]

$\Rightarrow \exists (\varepsilon, \alpha^-)$  DP protocol in (PKE - Dec) World

# PKE World



- ◆  $\forall (\varepsilon, \alpha)$  DP protocol in PKE World

[MMP14- TCC]

$\Rightarrow \exists (\varepsilon, \alpha^-)$  DP protocol in (RO + Test) World

# RO + Test World

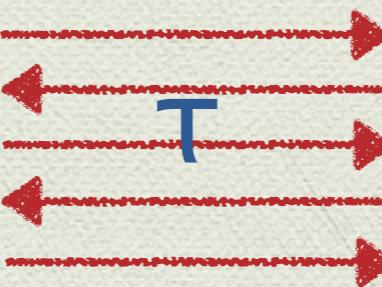
# RO + Test W

RO+Test

$d_1$



$V_A$

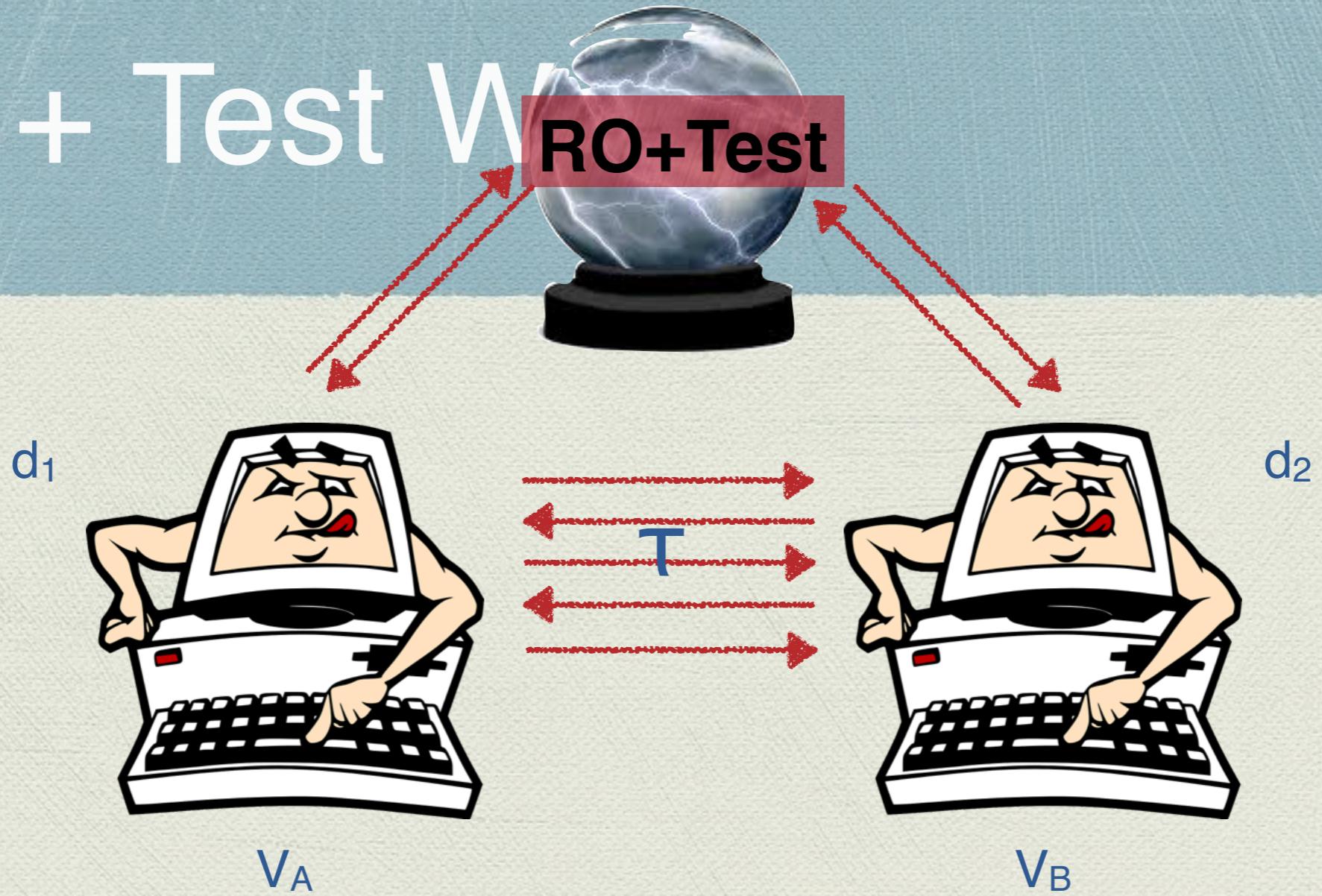


$d_2$



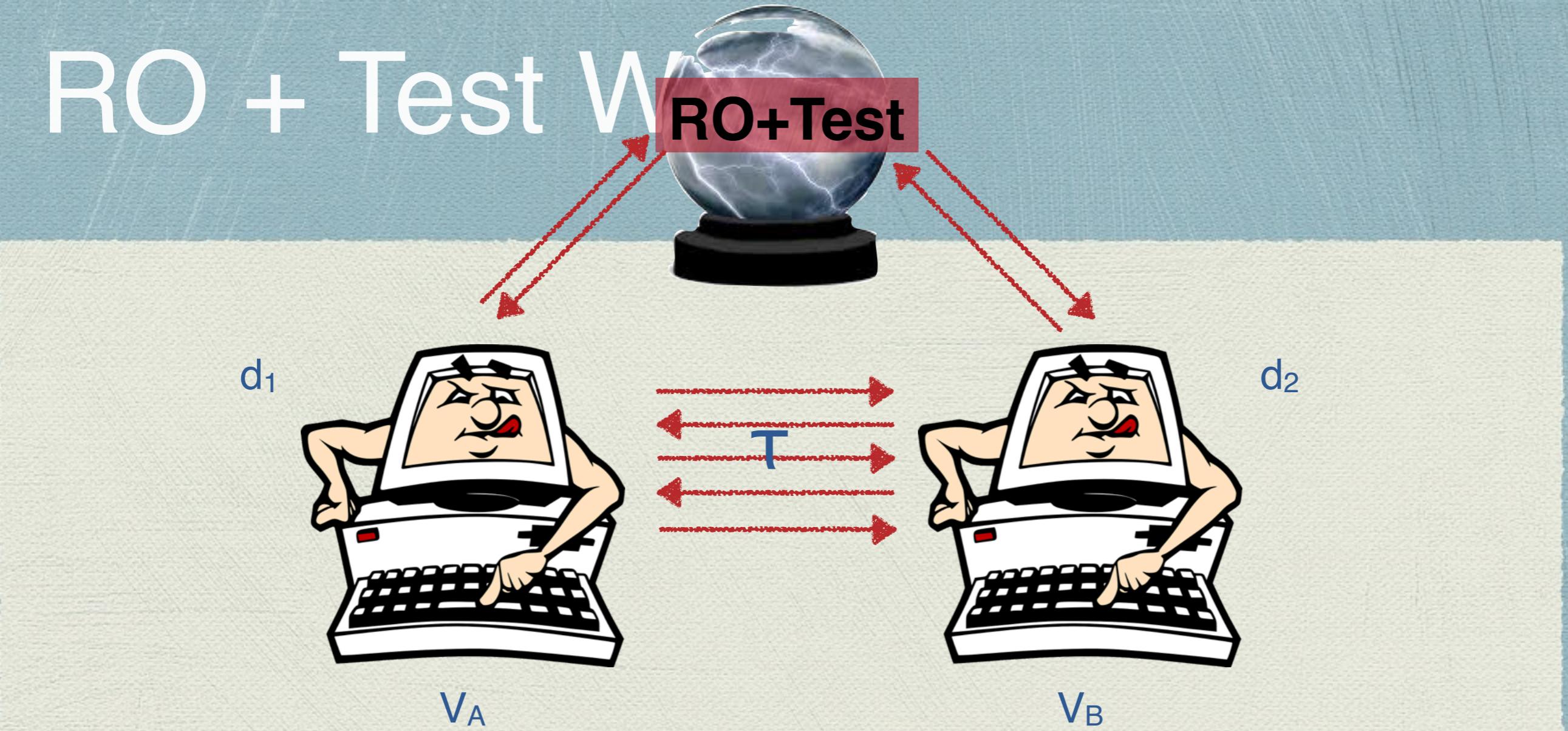
$V_B$

# RO + Test World



- $\forall (\varepsilon, \alpha^-)$  DP protocol in  $(RO + Test)$  World
- $\Rightarrow \exists (\varepsilon, \alpha^{--})$  DP protocol in  $(RO)$  World

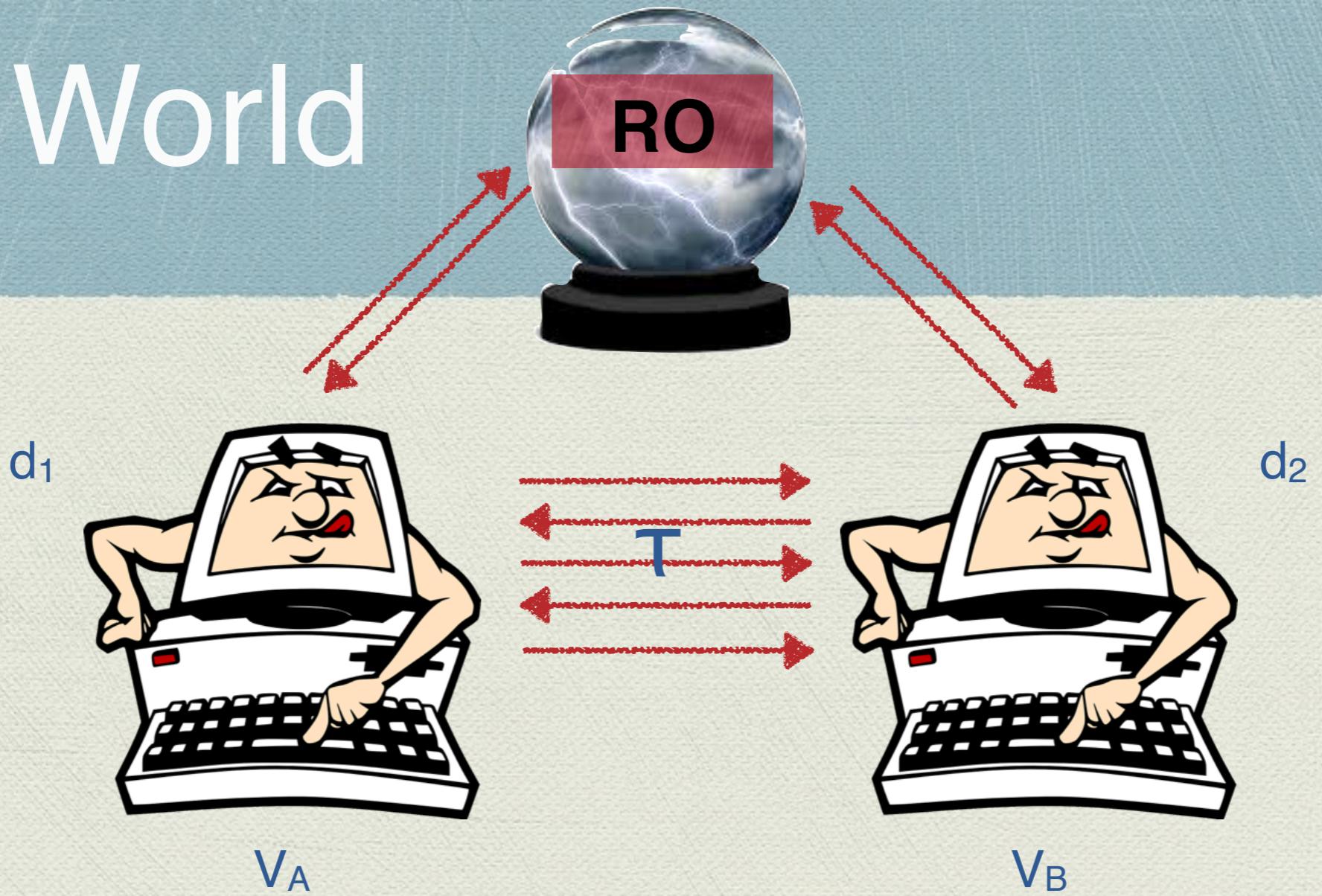
# RO + Test World



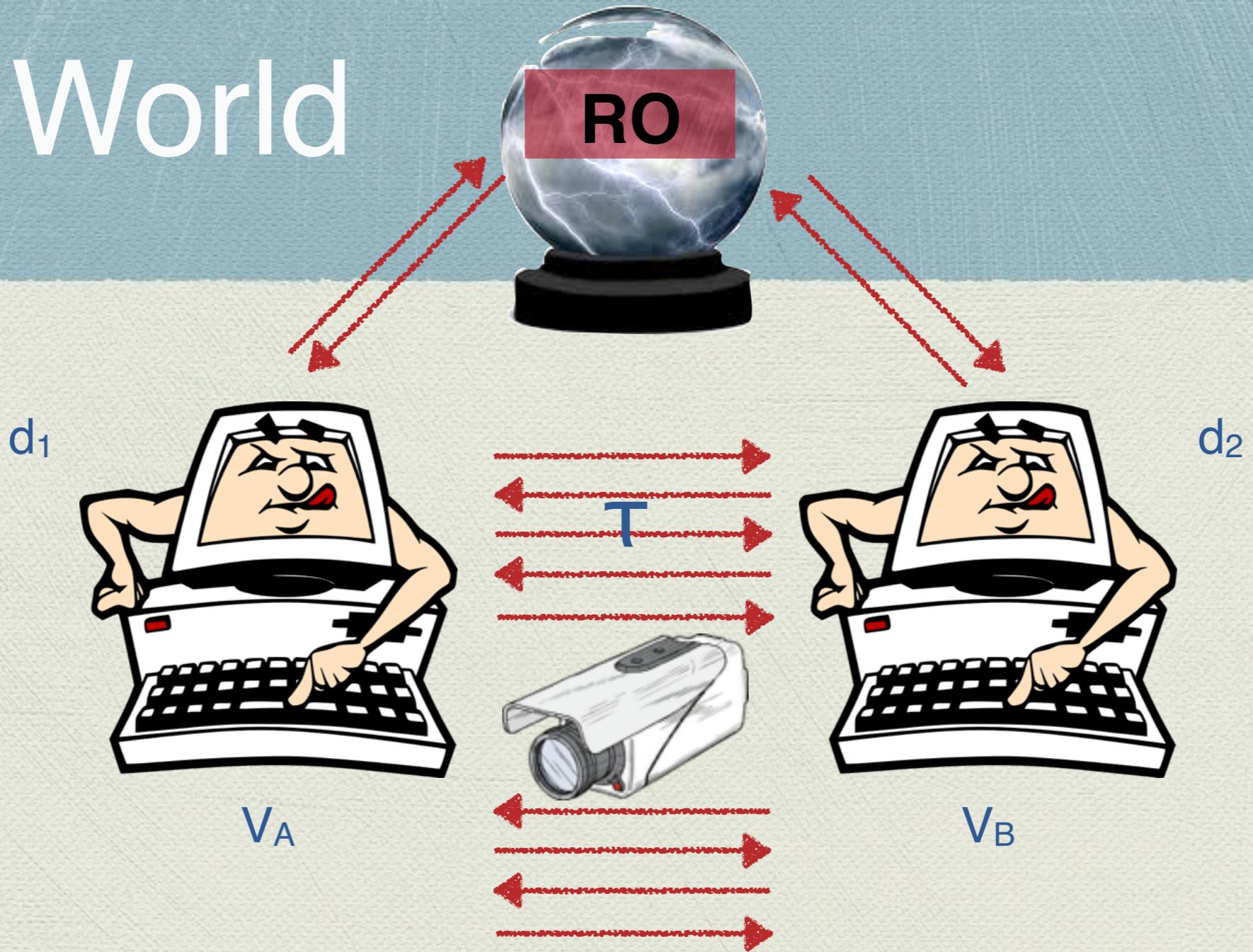
- $\forall (\varepsilon, \alpha^-)$  DP protocol in (RO + Test) World  
[MMP14- TCC]
- ⇒  $\exists (\varepsilon, \alpha^{--})$  DP protocol in (RO) World

# RO World

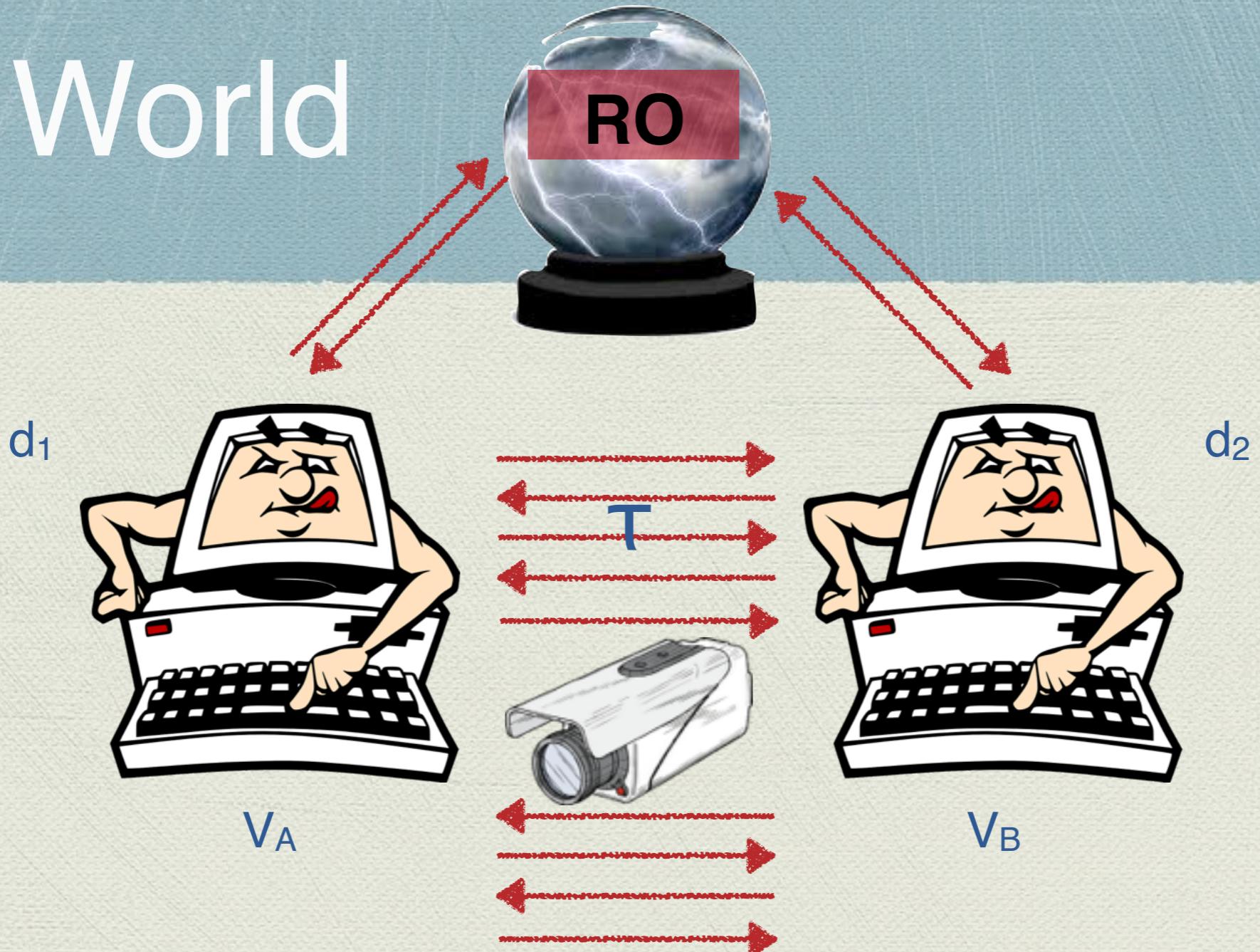
# RO World



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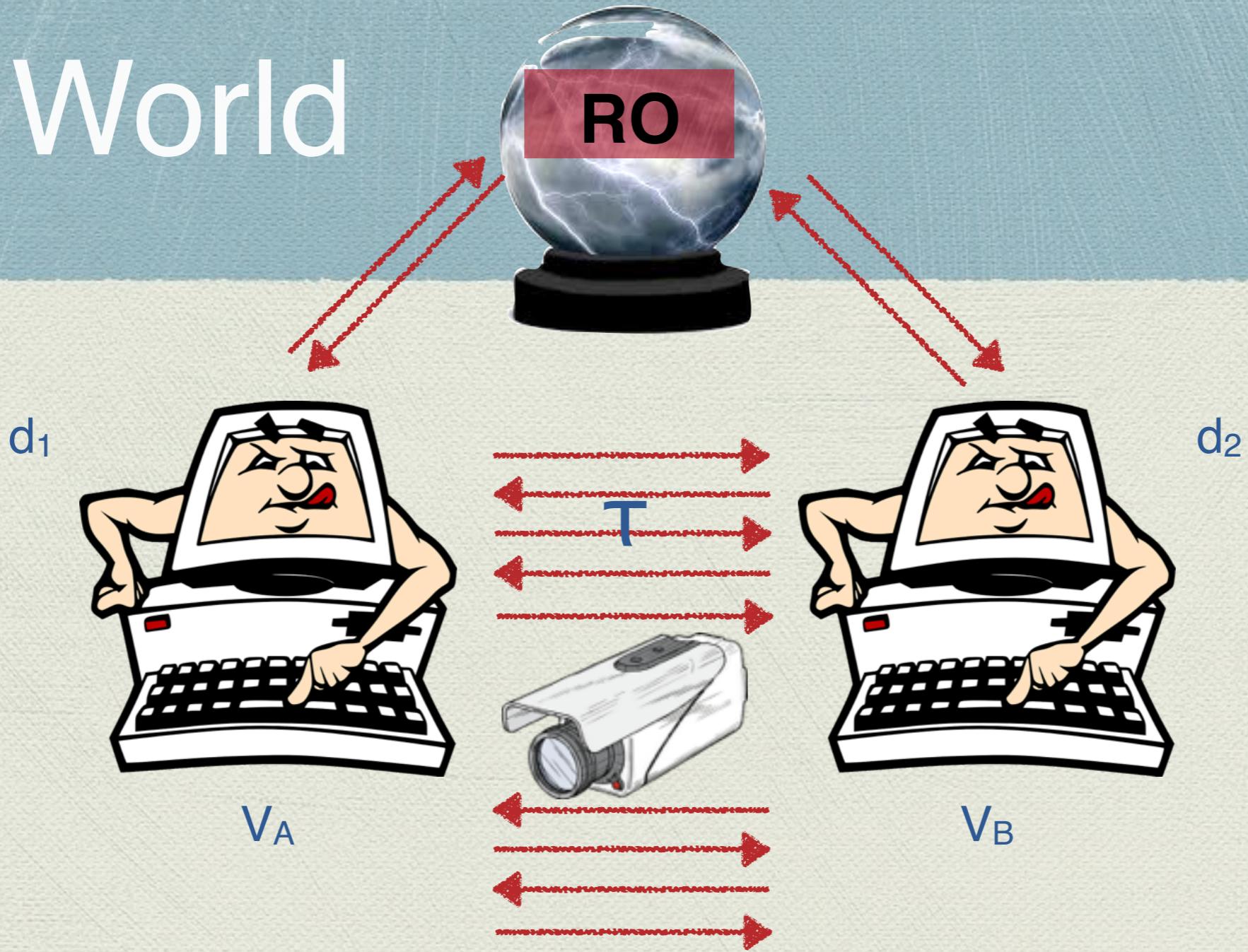


# RO World



[MMP14- ITCS]

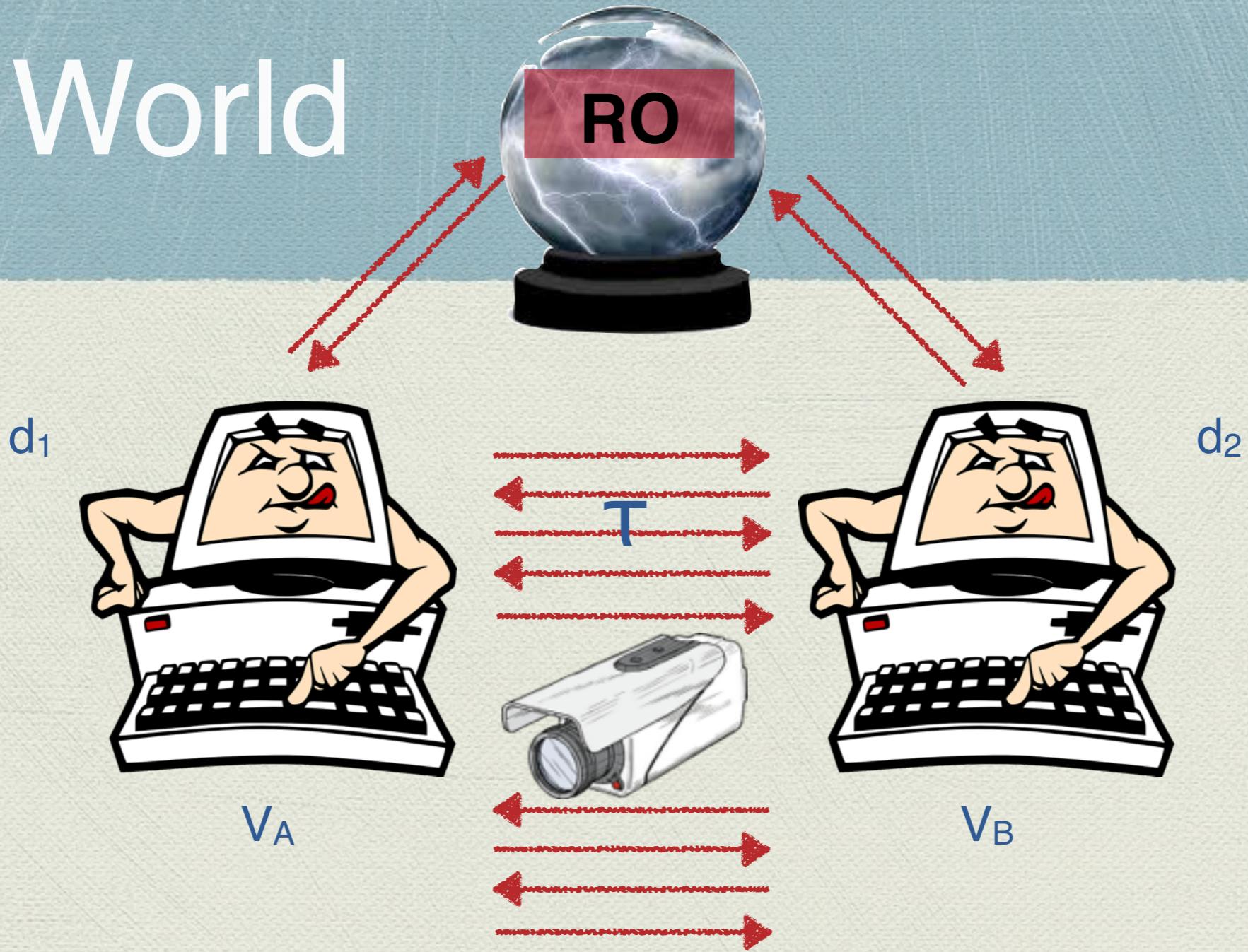
# RO World



- ◆ Near-independence in RO World [MMP14- ITCS]

$$\Rightarrow \alpha_{\text{RO}, f, \varepsilon}^{(\max)} = (\alpha_{\text{IT}, f, \varepsilon}^{(\max)})^+$$

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[GMPS13]

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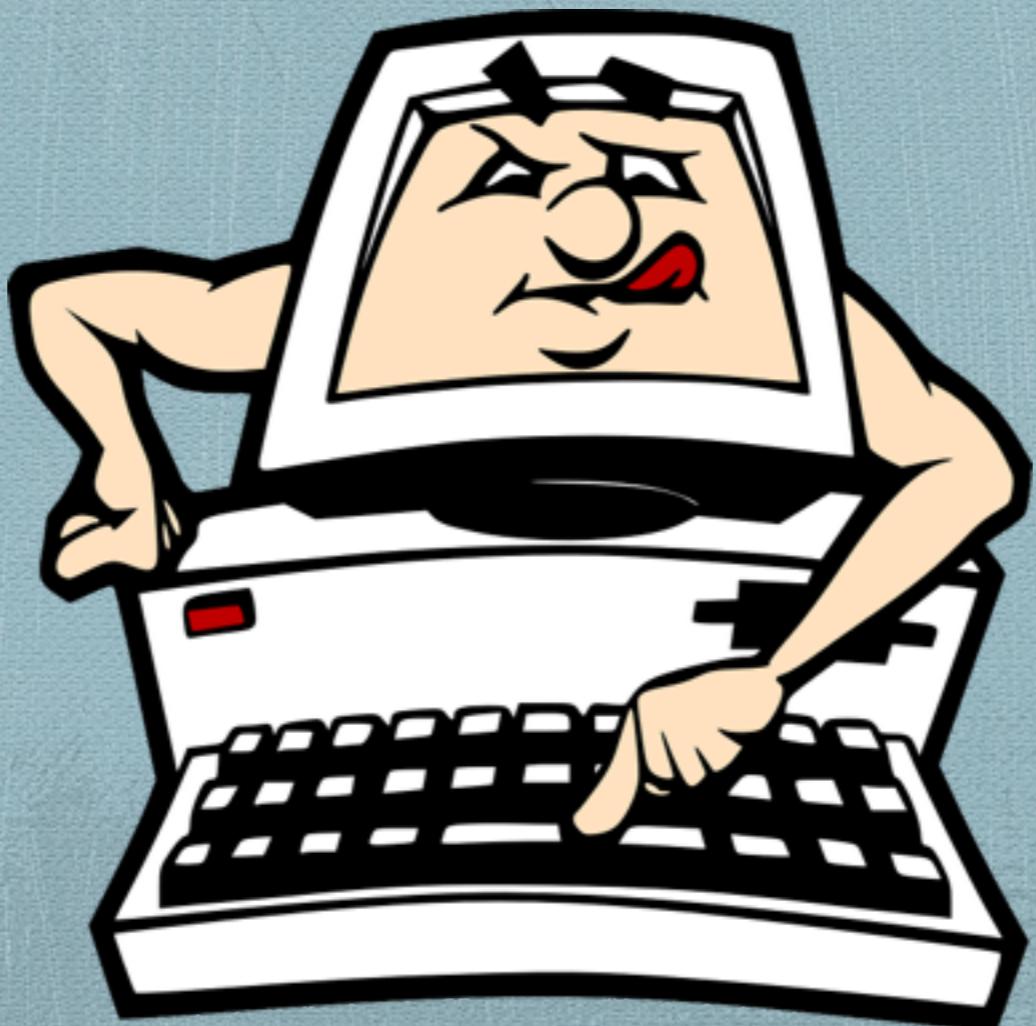
- ◆  $(\varepsilon, \alpha)$  DP in PKE World  $\Rightarrow (\varepsilon, \alpha^{--})$  DP in RO World  
 $\Rightarrow \alpha_{\text{PKE}, f, \varepsilon}^{(\max)} = (\alpha_{\text{RO}, f, \varepsilon}^{(\max)})^+$

# Putting it all together,

- ◆  $(\varepsilon, \alpha)$  DP in PKE World  $\Rightarrow (\varepsilon, \alpha^{--})$  DP in RO World  
 $\Rightarrow \alpha_{PKE,f,\varepsilon}^{(\max)} = (\alpha_{RO,f,\varepsilon}^{(\max)})^+$
- ◆ Near independence in RO world  
 $\Rightarrow \alpha_{RO,f,\varepsilon}^{(\max)} = (\alpha_{IT,f,\varepsilon}^{(\max)})^+ \ll \alpha_{f,\varepsilon}^{(\text{opt})}$

# Putting it all together,

- ◆  $(\varepsilon, \alpha)$  DP in PKE World  $\Rightarrow (\varepsilon, \alpha^{--})$  DP in RO World  
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 $\Rightarrow \alpha_{RO,f,\varepsilon}^{(\max)} = (\alpha_{IT,f,\varepsilon}^{(\max)})^+ \ll \alpha_{f,\varepsilon}^{(\text{opt})}$
- ◆  $\Rightarrow \alpha_{PKE,f,\varepsilon}^{(\max)} = (\alpha_{IT,f,\varepsilon}^{(\max)})^{++} \ll \alpha_{f,\varepsilon}^{(\text{opt})}$



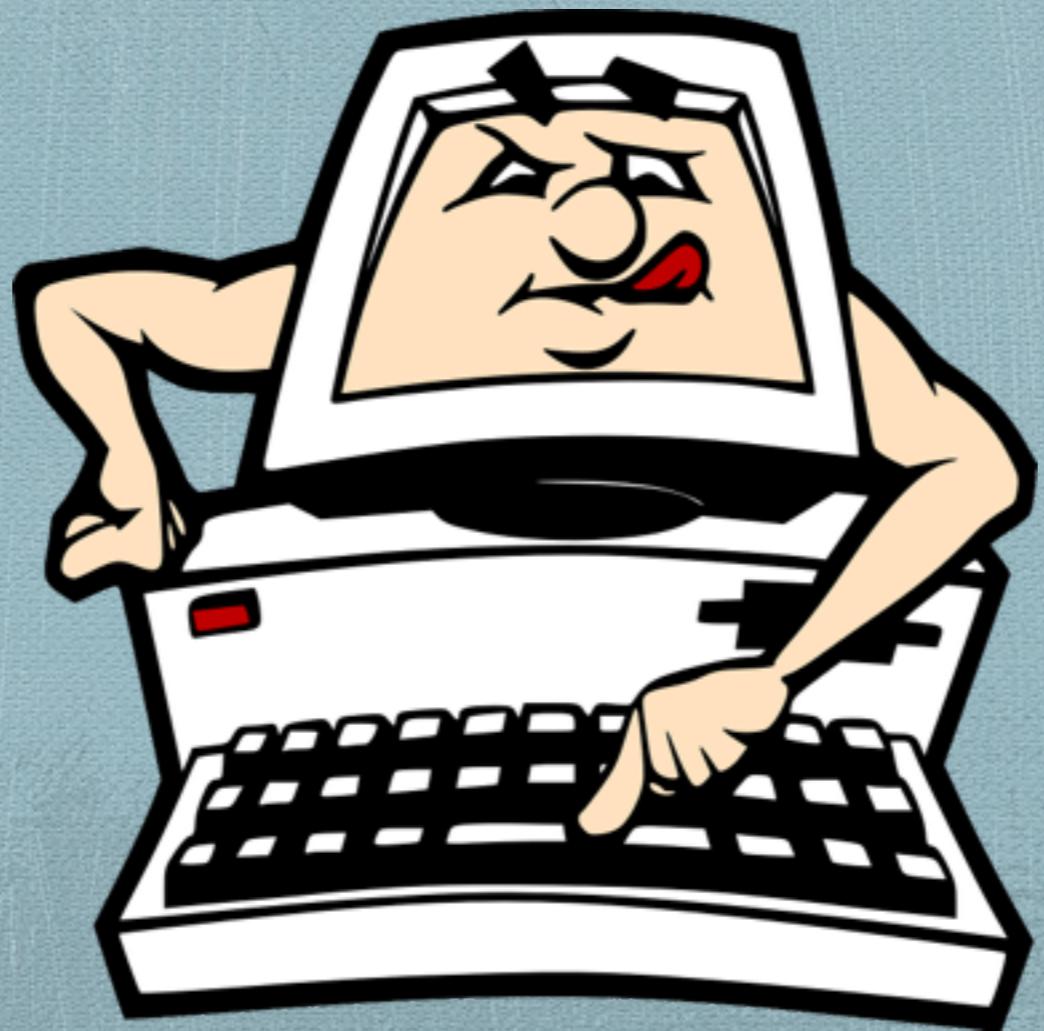
# Conclusion

# Technical Recap

- ◆ PKE Oracle = (Gen, Enc, Dec, Test<sub>1</sub>, Test<sub>2</sub>)
- ◆ PKE = (RO + Test + Dec)  $\approx$  RO + Test  $\approx$  RO  
[MMP14- TCC]
- ◆ (Nearly) Independent views in RO world  
[MMP14- ITCS]
- ◆ (Mimic) IT impossibility [GMPS13]

# Open Questions

- ◆ Does optimally accurate distributed DP  $\Rightarrow$  OT?
  - ◆ Use Key Agreement in **non black-box** way
  - ◆ **New intermediate computational assumptions** equivalent to optimal distributed DP
  - ◆ New techniques to **obtain OT** from properties
    - ◆ Similar problems in **optimal fair coin tossing**



Thank You