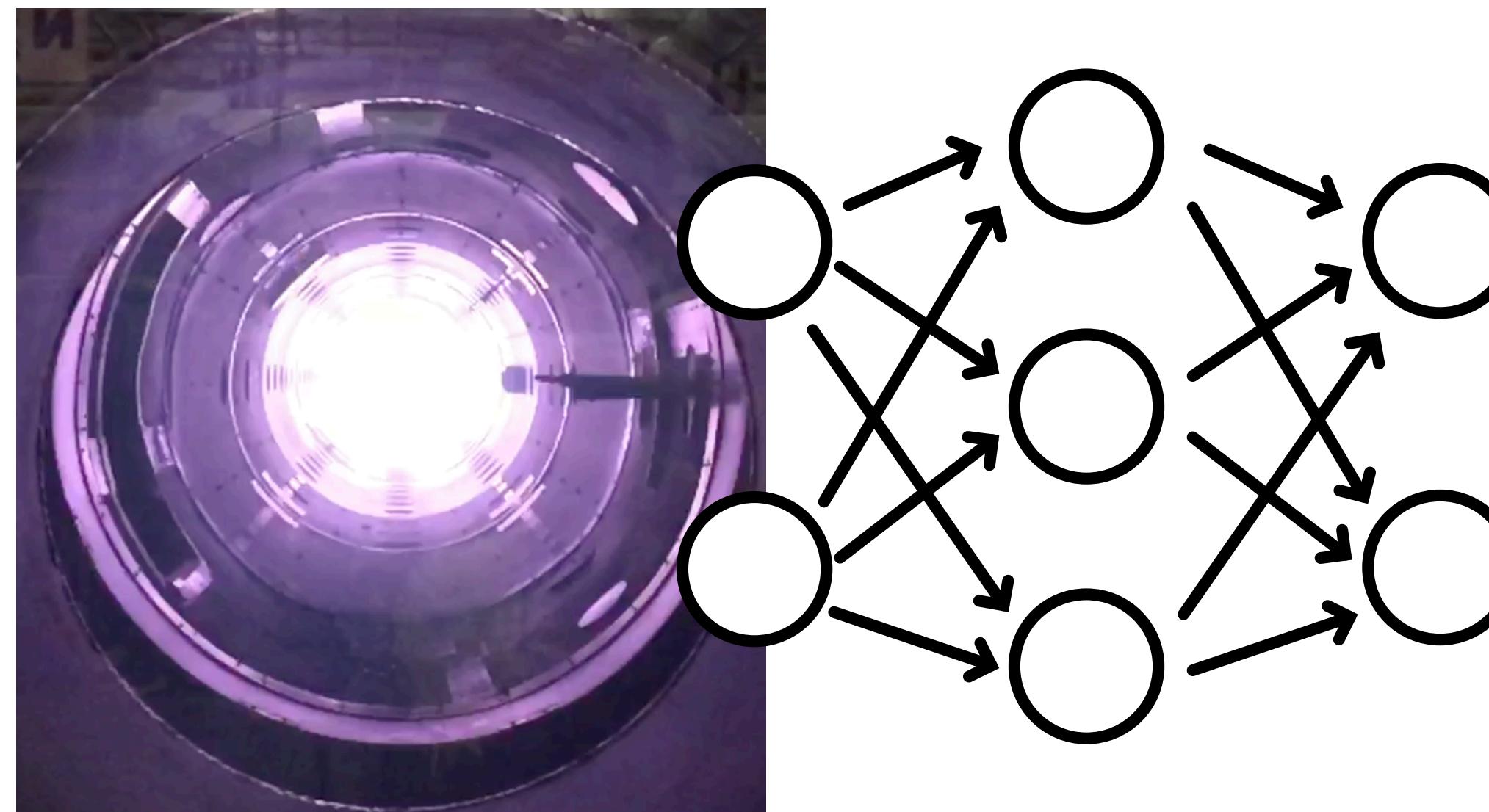


# Autosweep: automated Langmuir sweep analysis



Phil Travis  
[phil@physics.ucla.edu](mailto:phil@physics.ucla.edu)  
APS DPP, November 10th, 2020



U.S. DEPARTMENT OF  
**ENERGY**

Office of  
Science

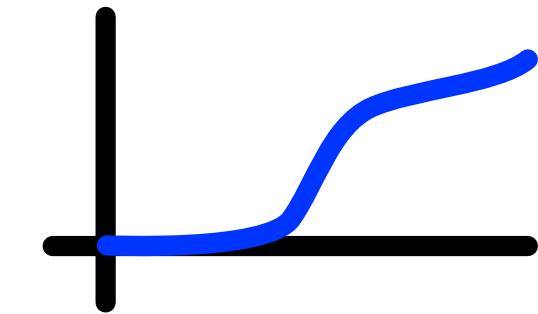
Work supported by the US DOE and NSF, and performed  
at the Basic Plasma Science Facility (BaPSF), UCLA.

# Autosweep: automated Langmuir sweep analysis

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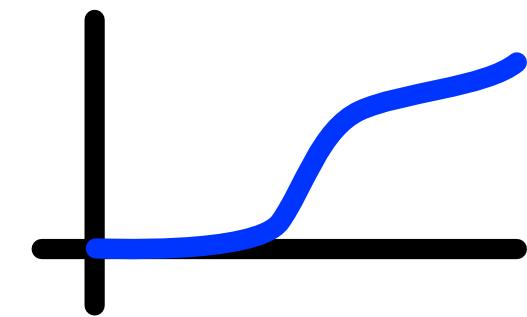
- Langmuir sweeps measure  $T_e$  and  $V_p$  in the LAPD



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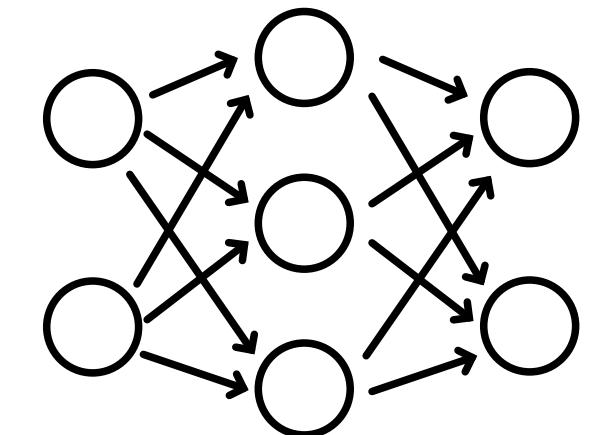
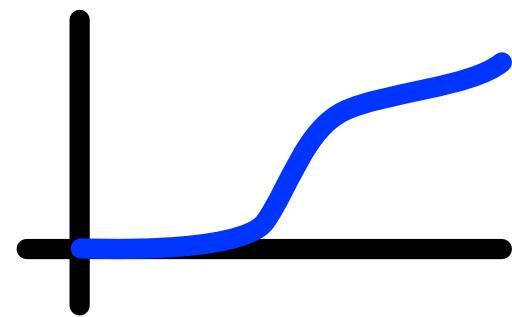
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- ... which can be difficult to analyze because of fluctuations



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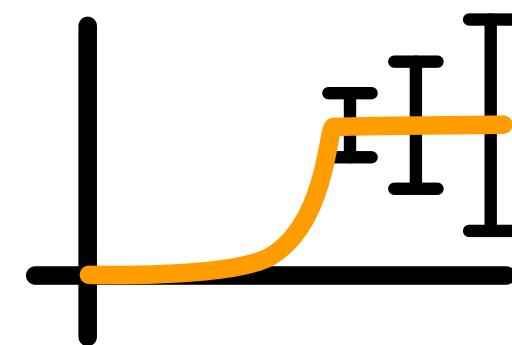
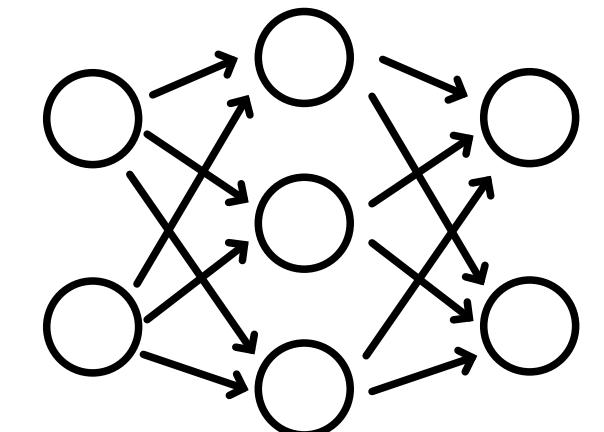
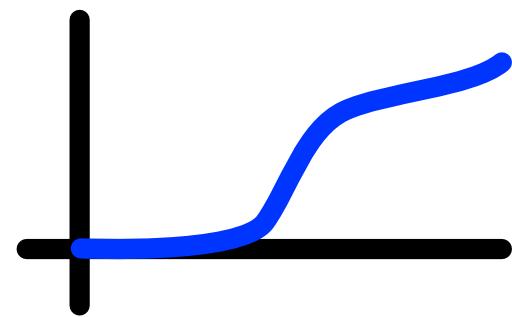
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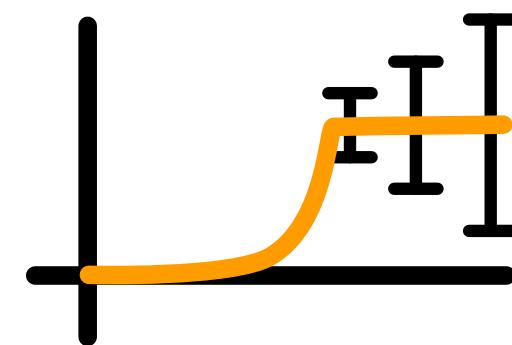
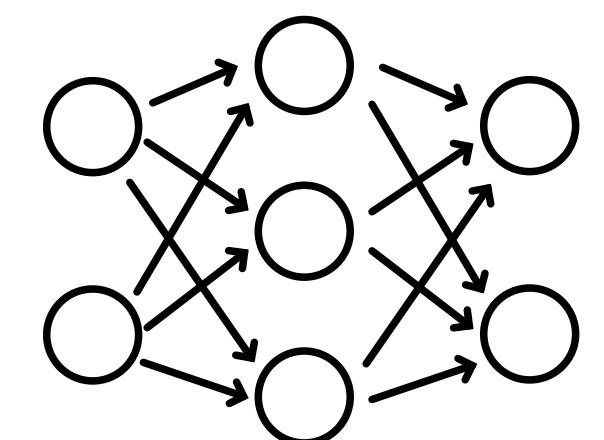
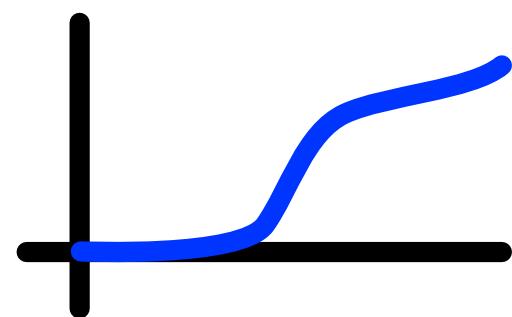
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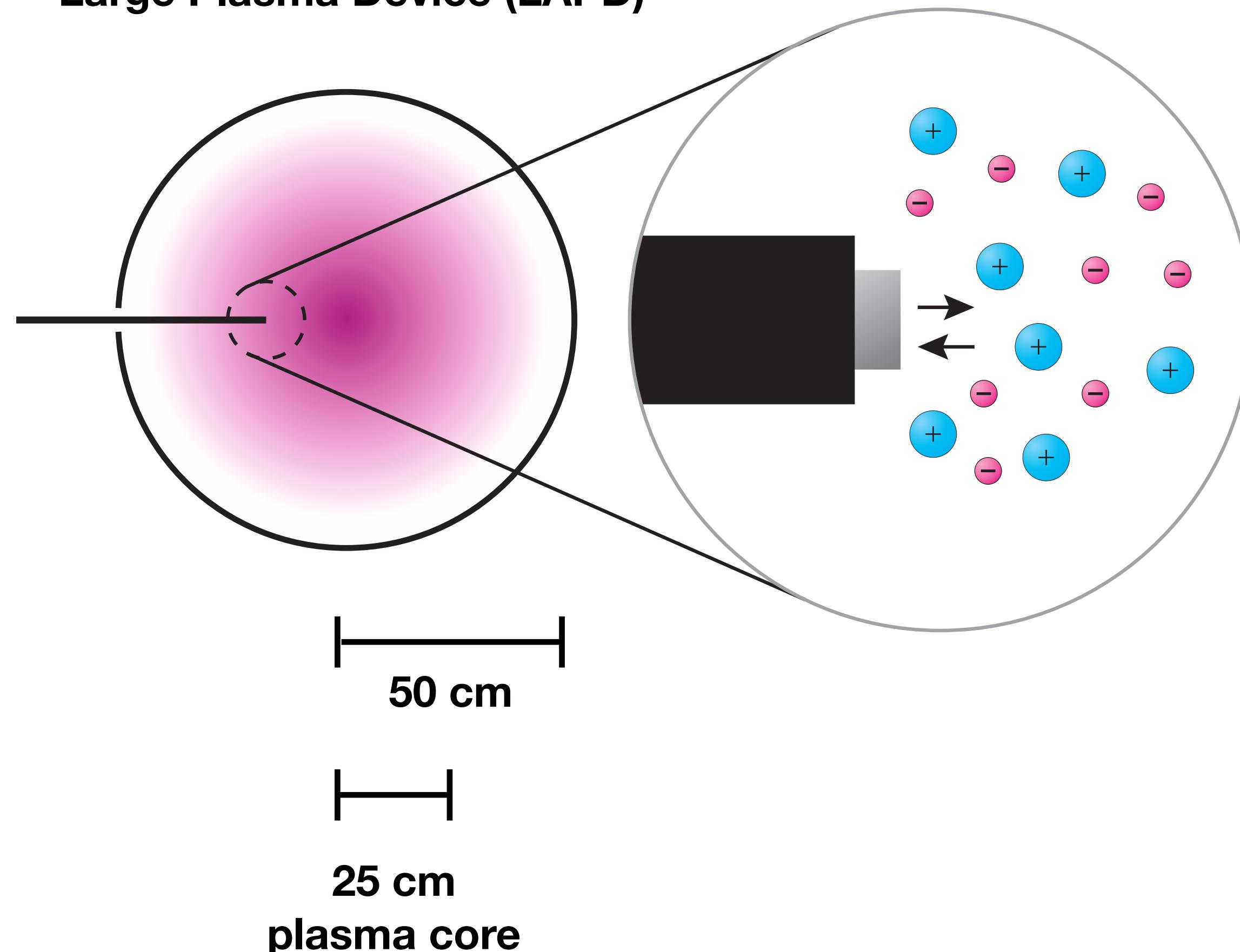
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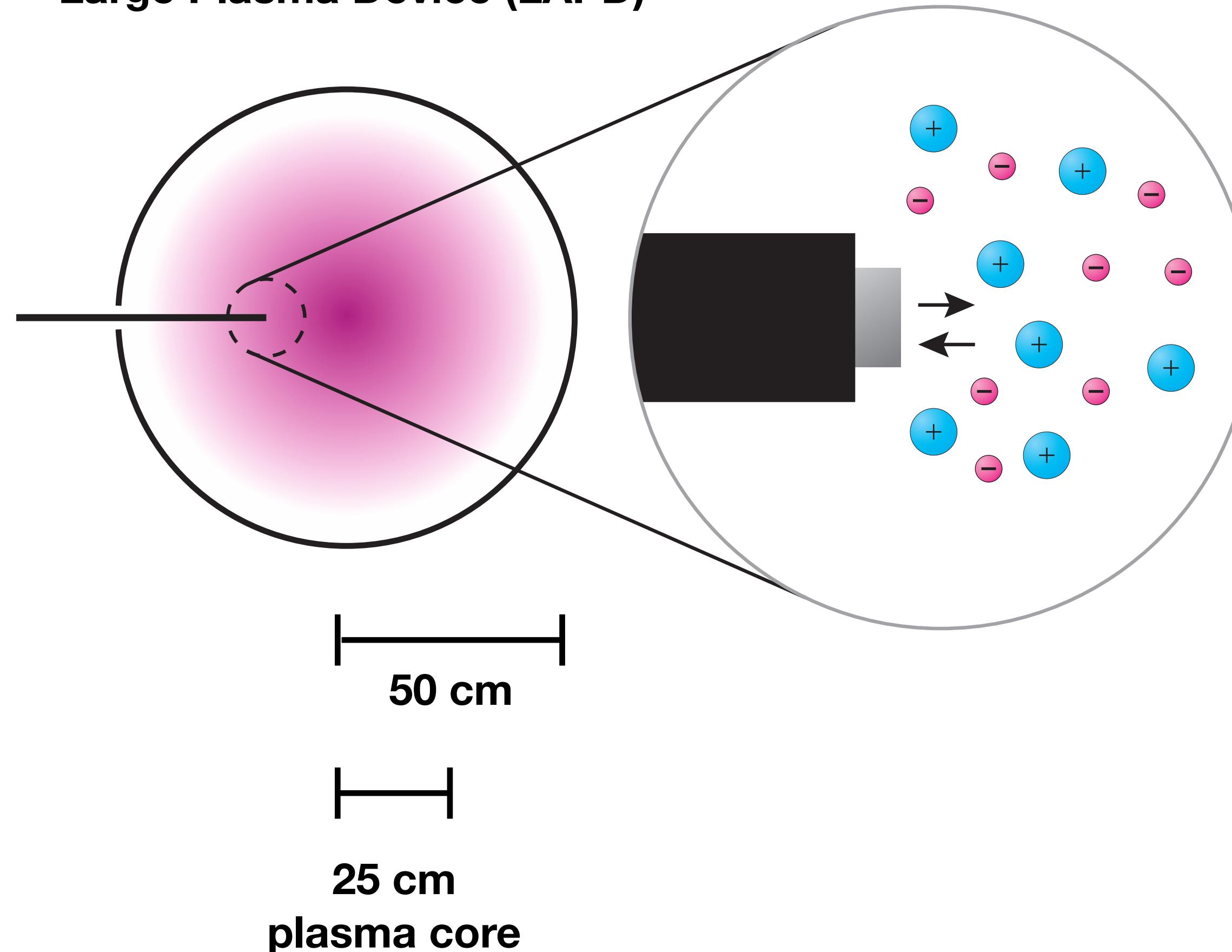
# Plasma parameters can be measured with Langmuir probes

**Large Plasma Device (LAPD)**



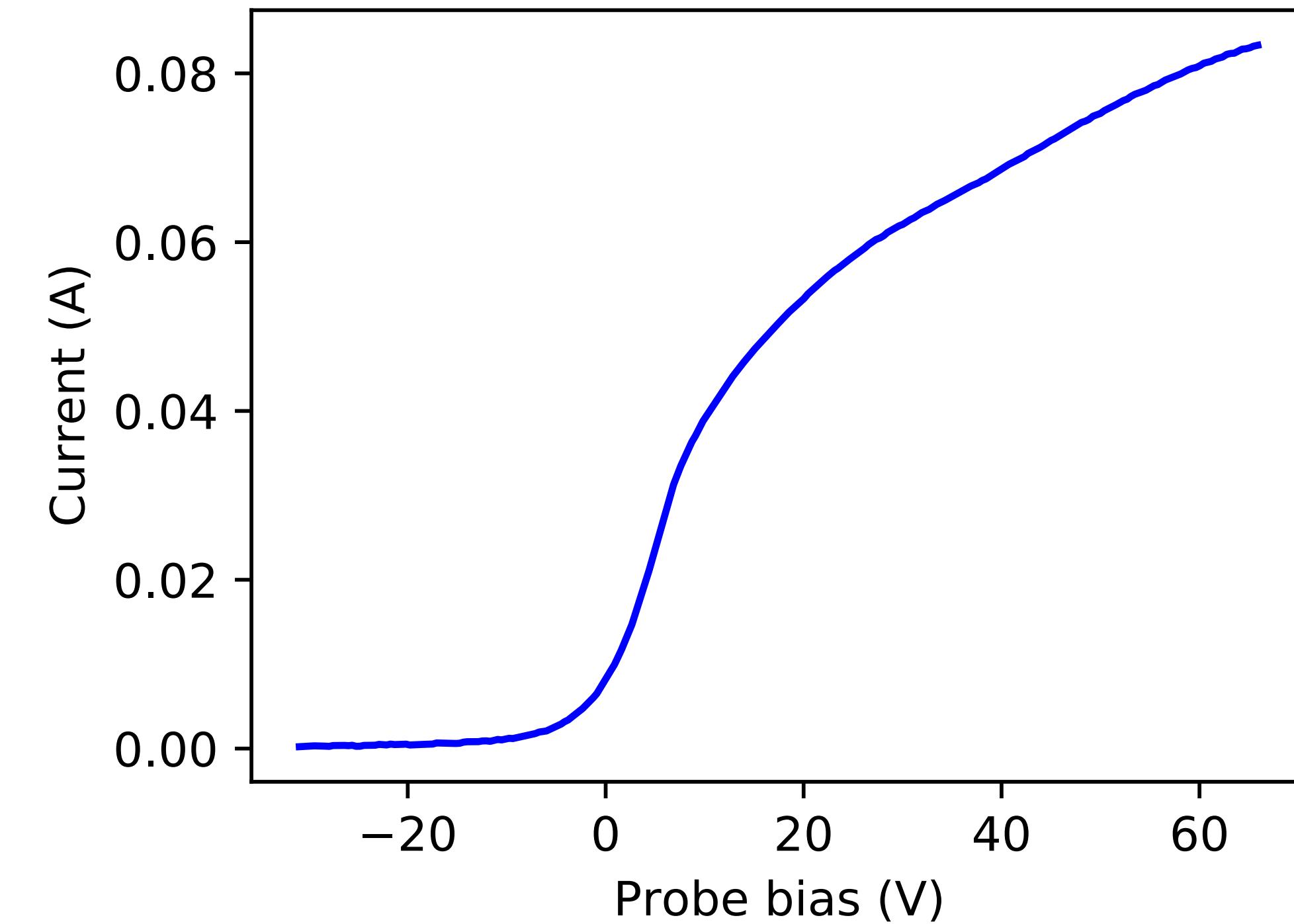
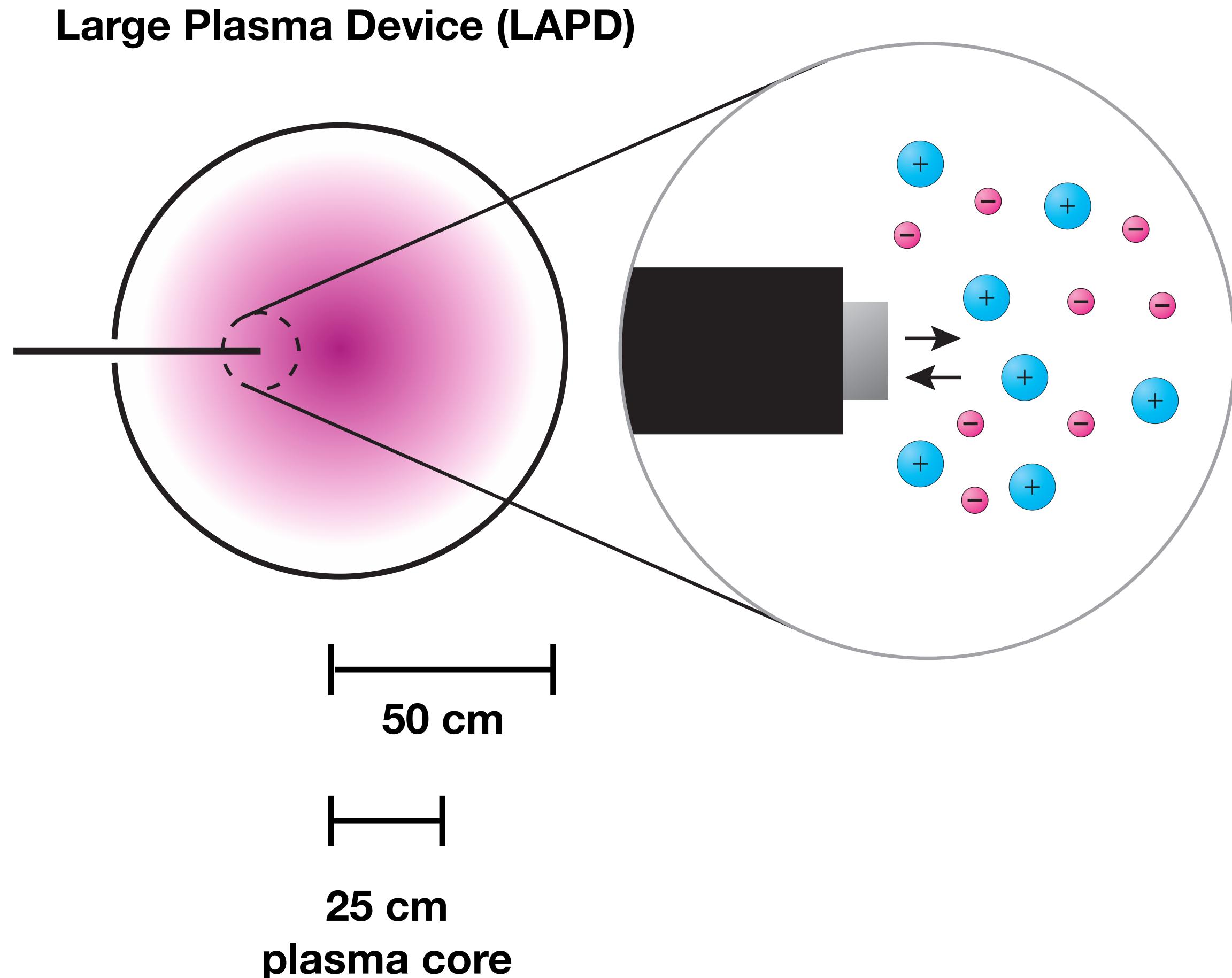
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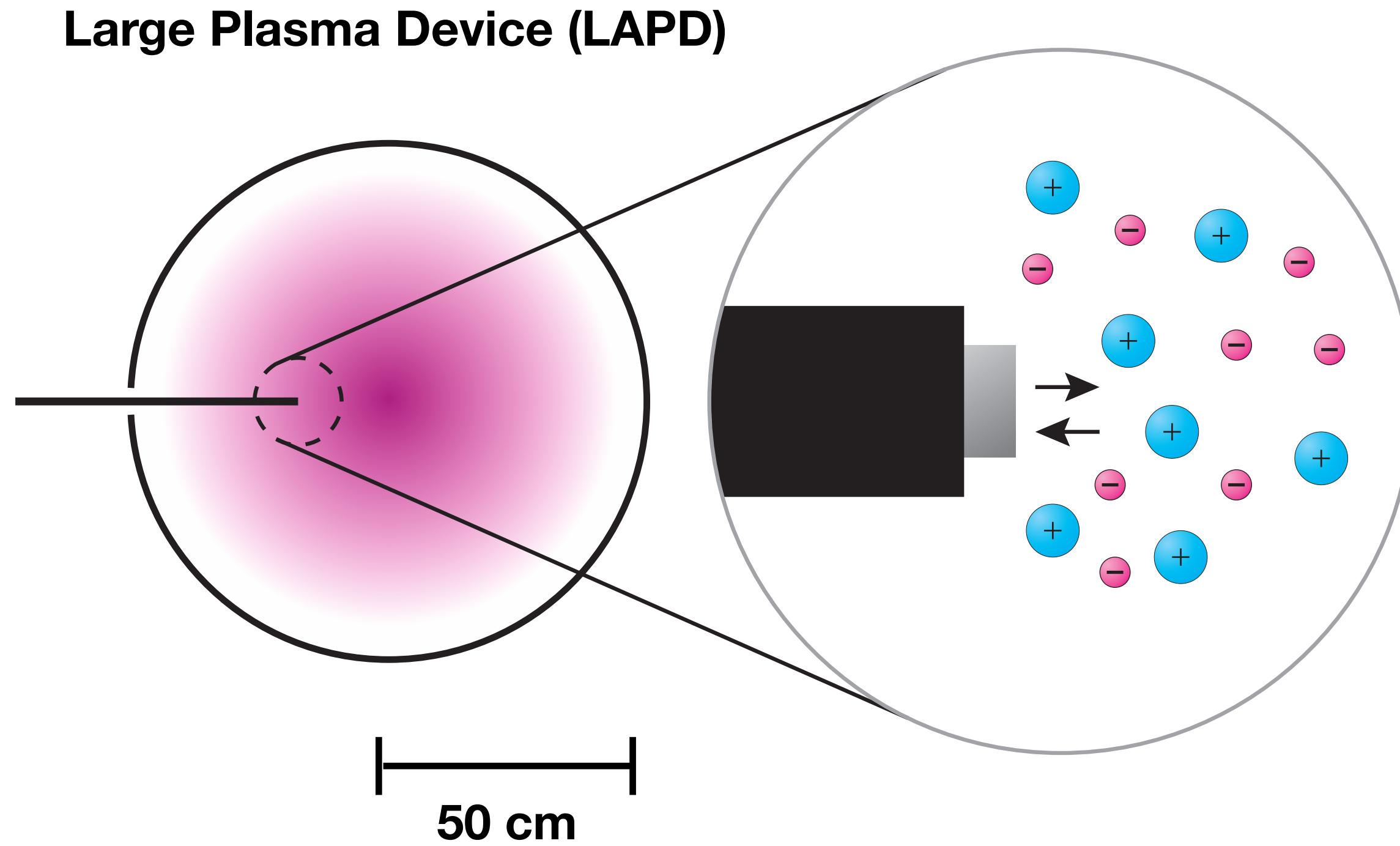
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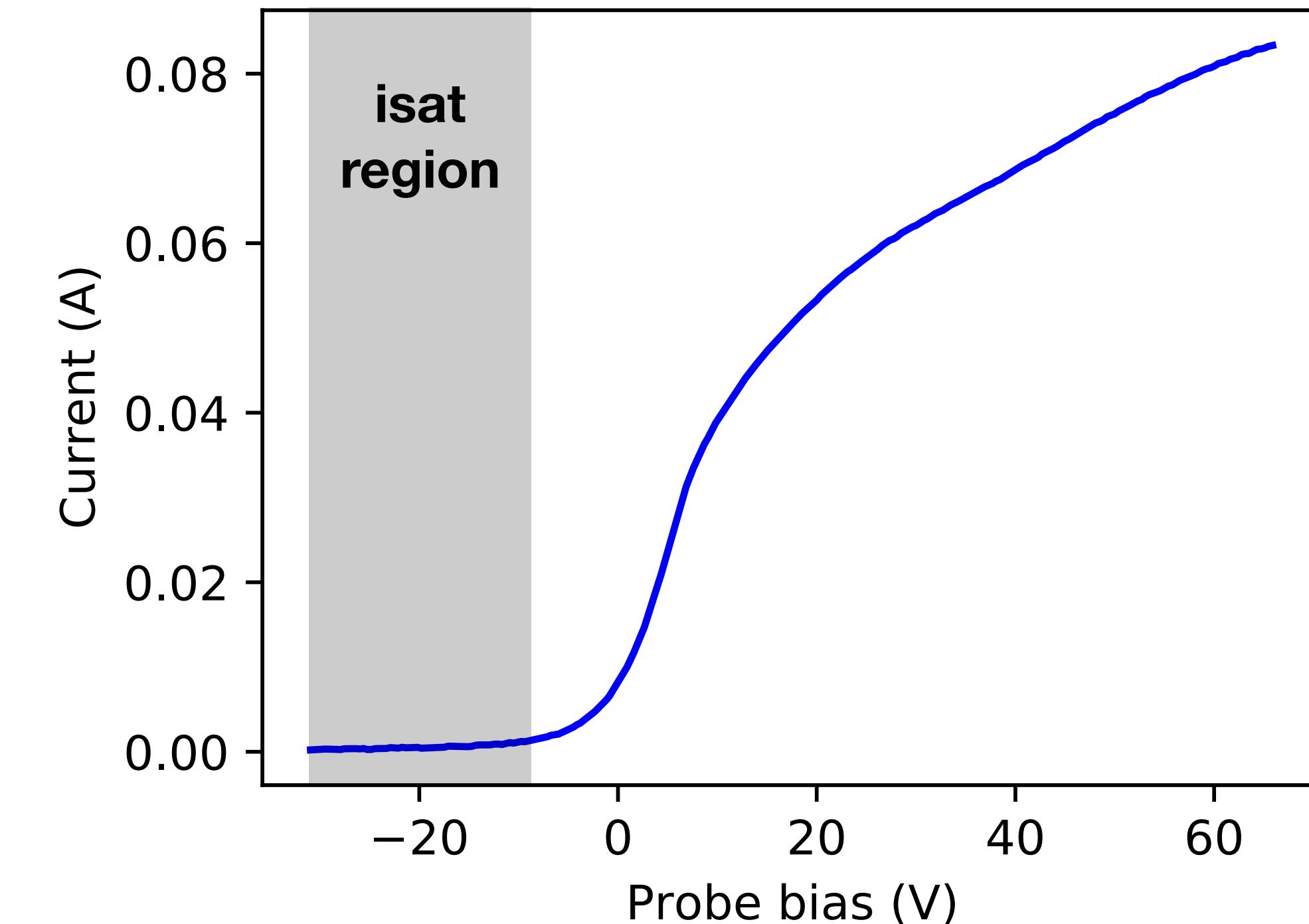


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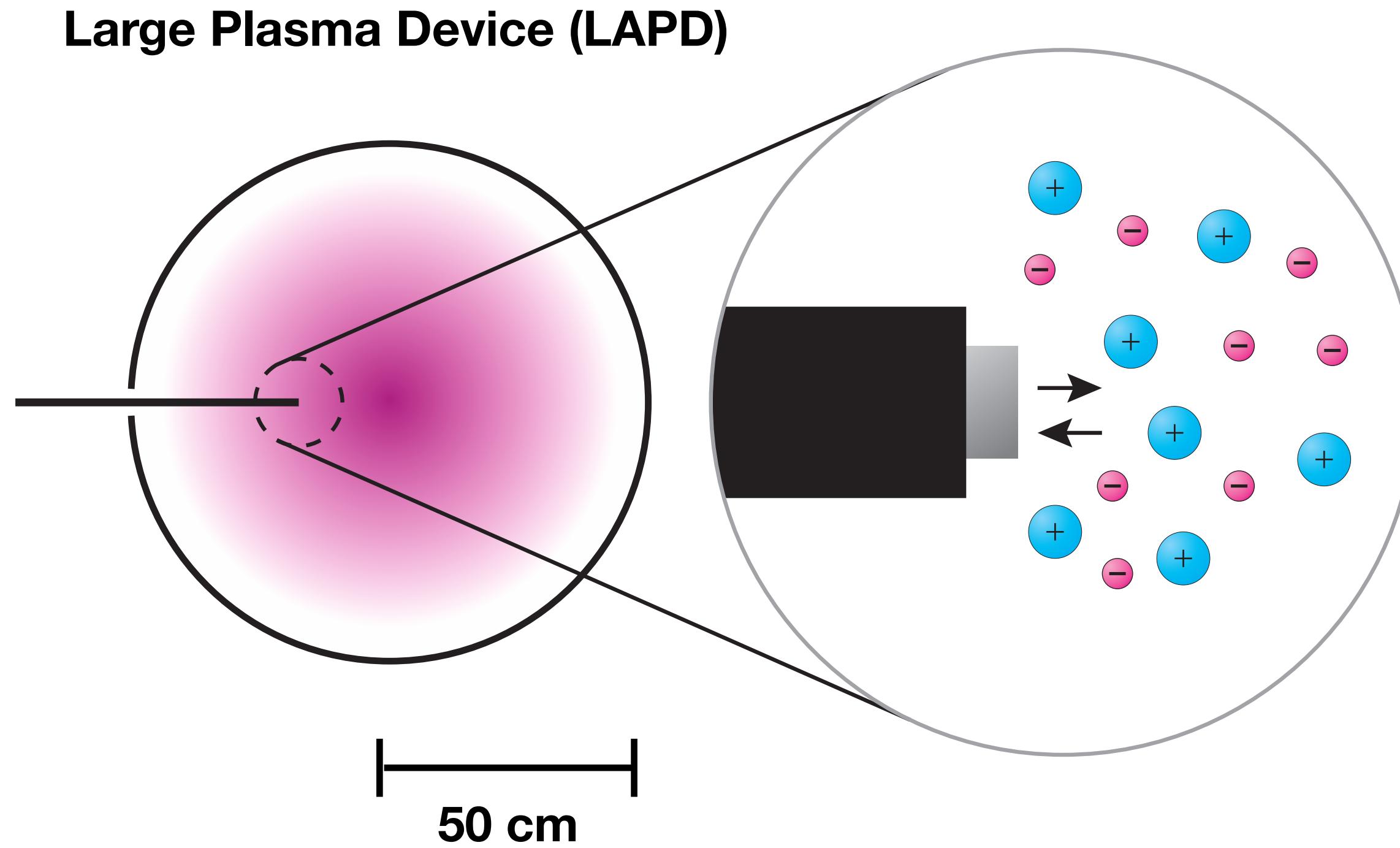


25 cm  
plasma core

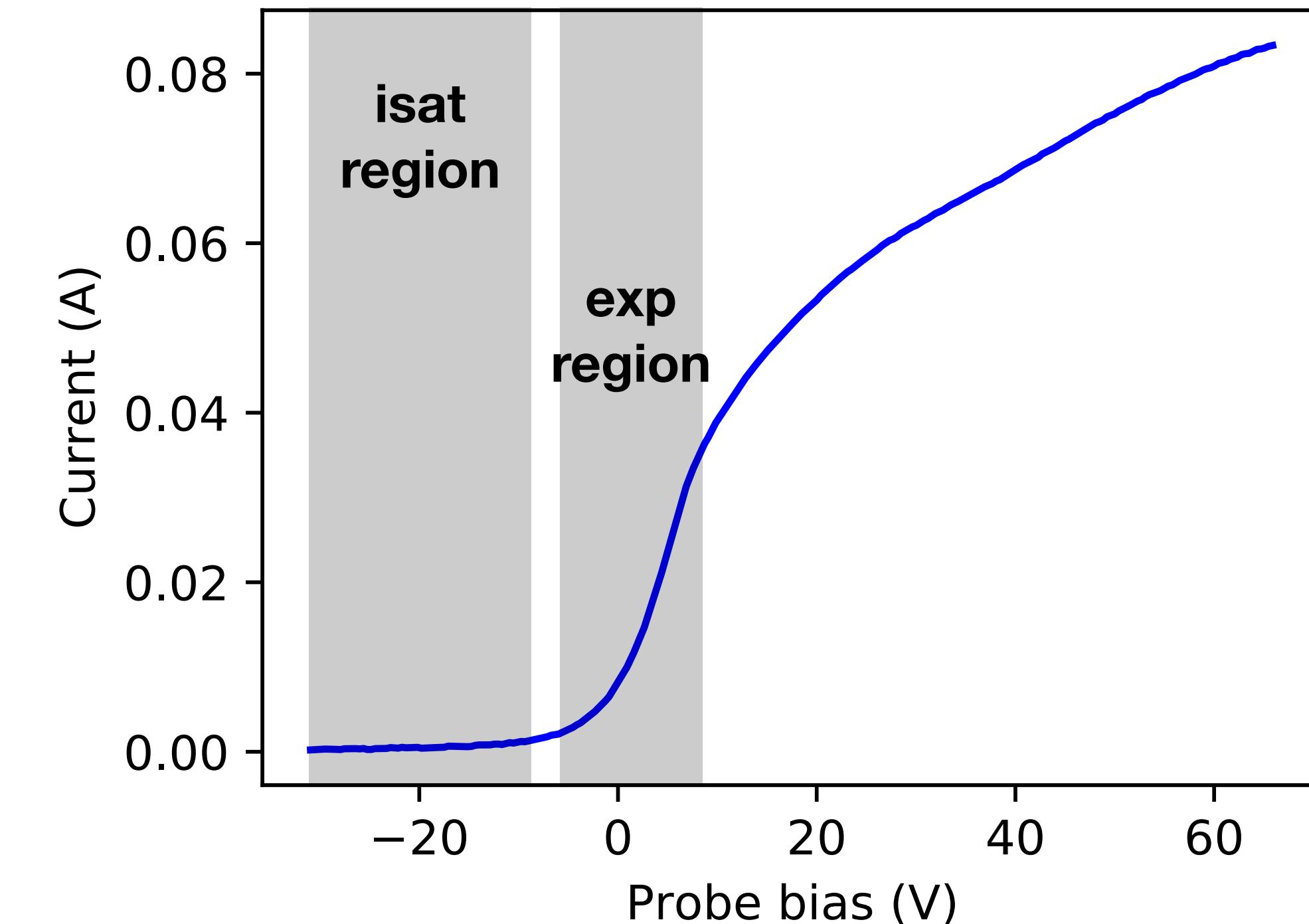


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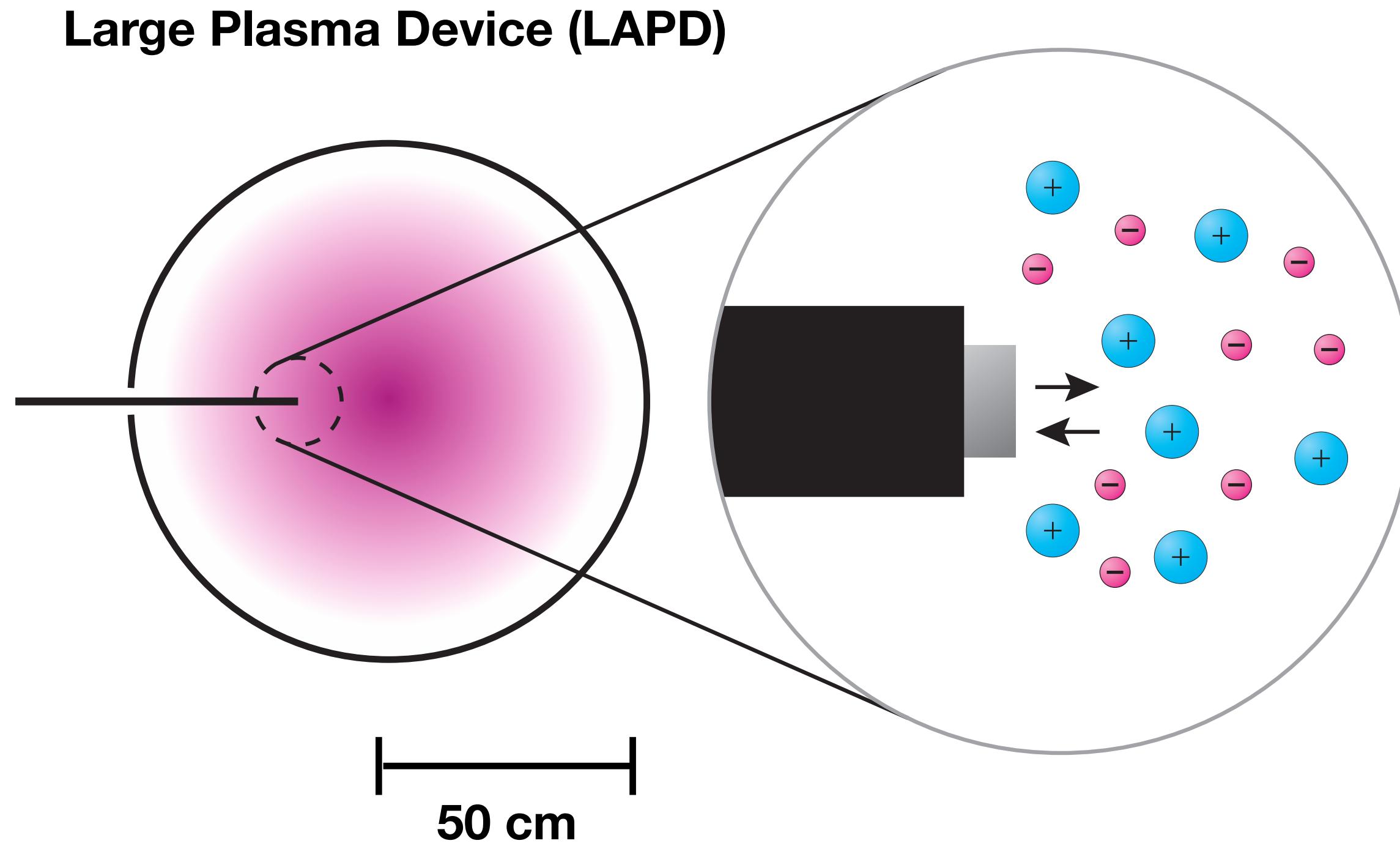


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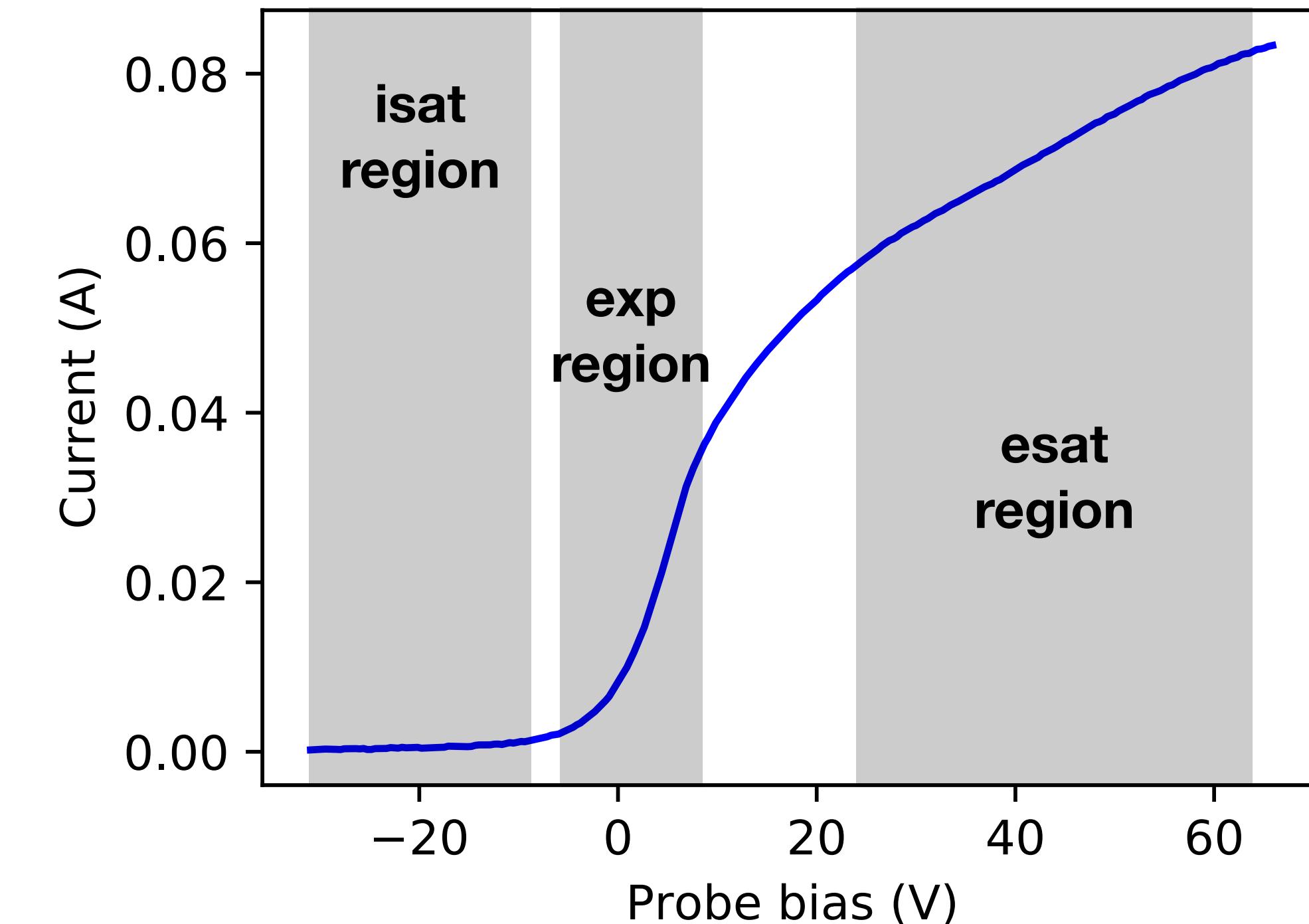


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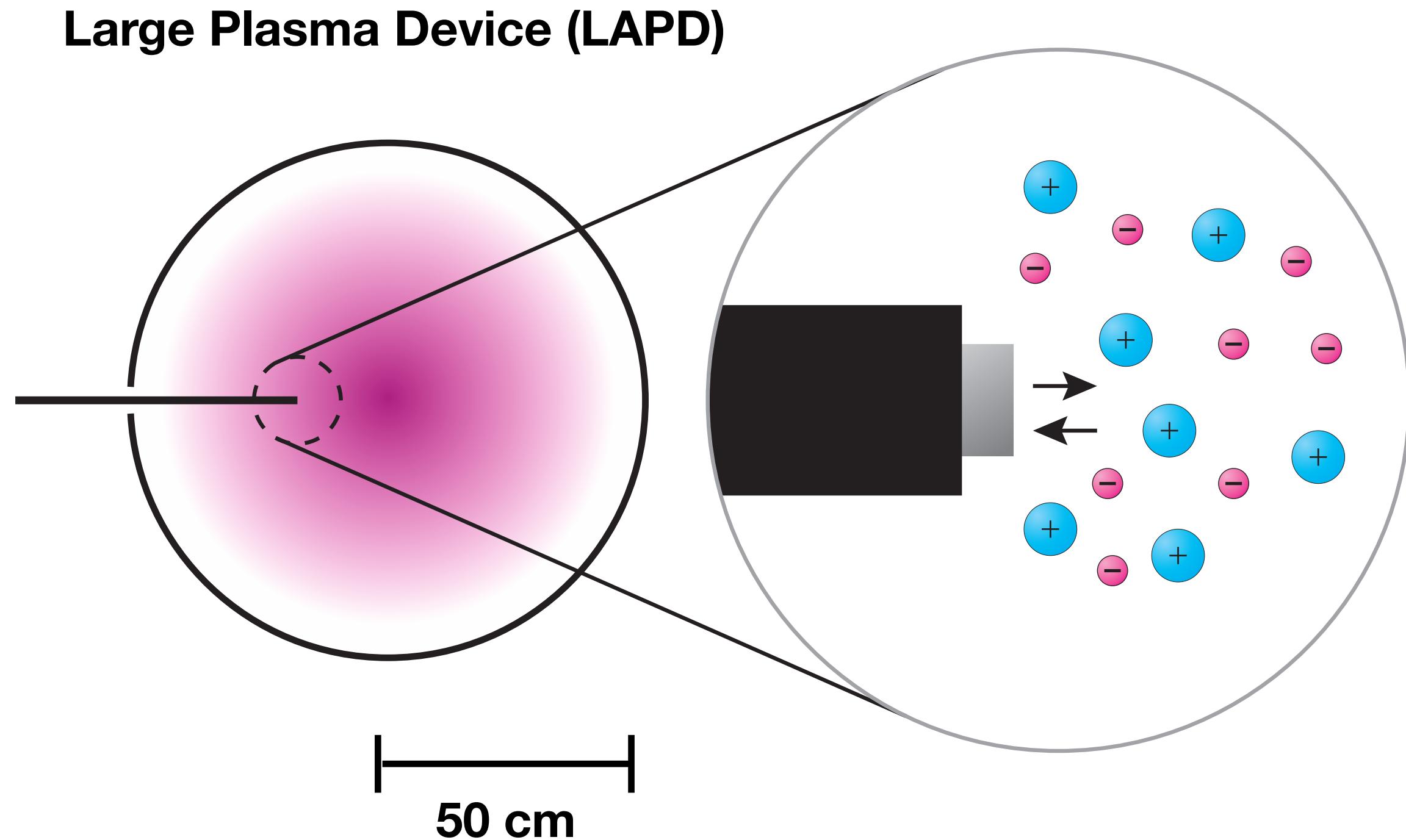


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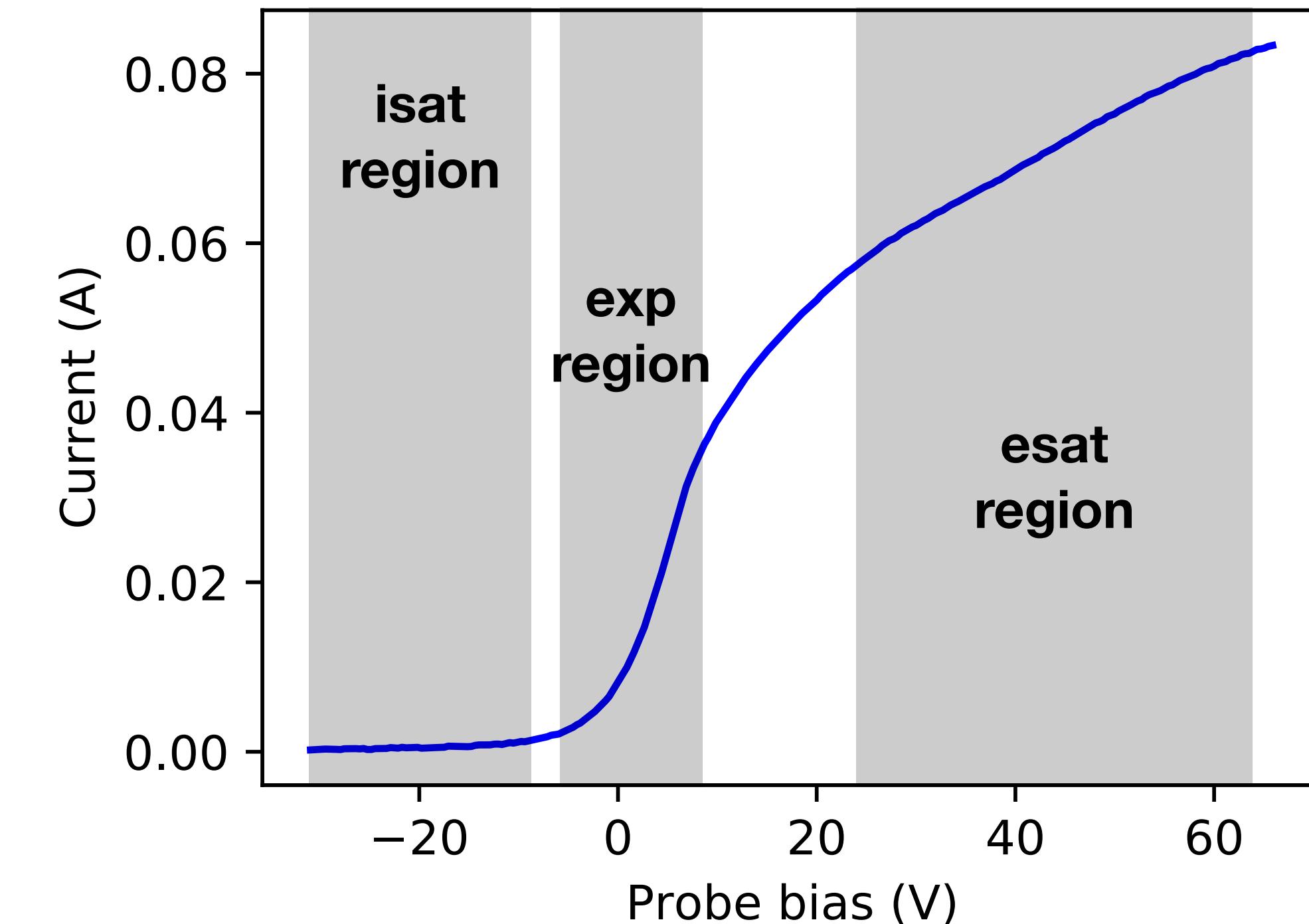
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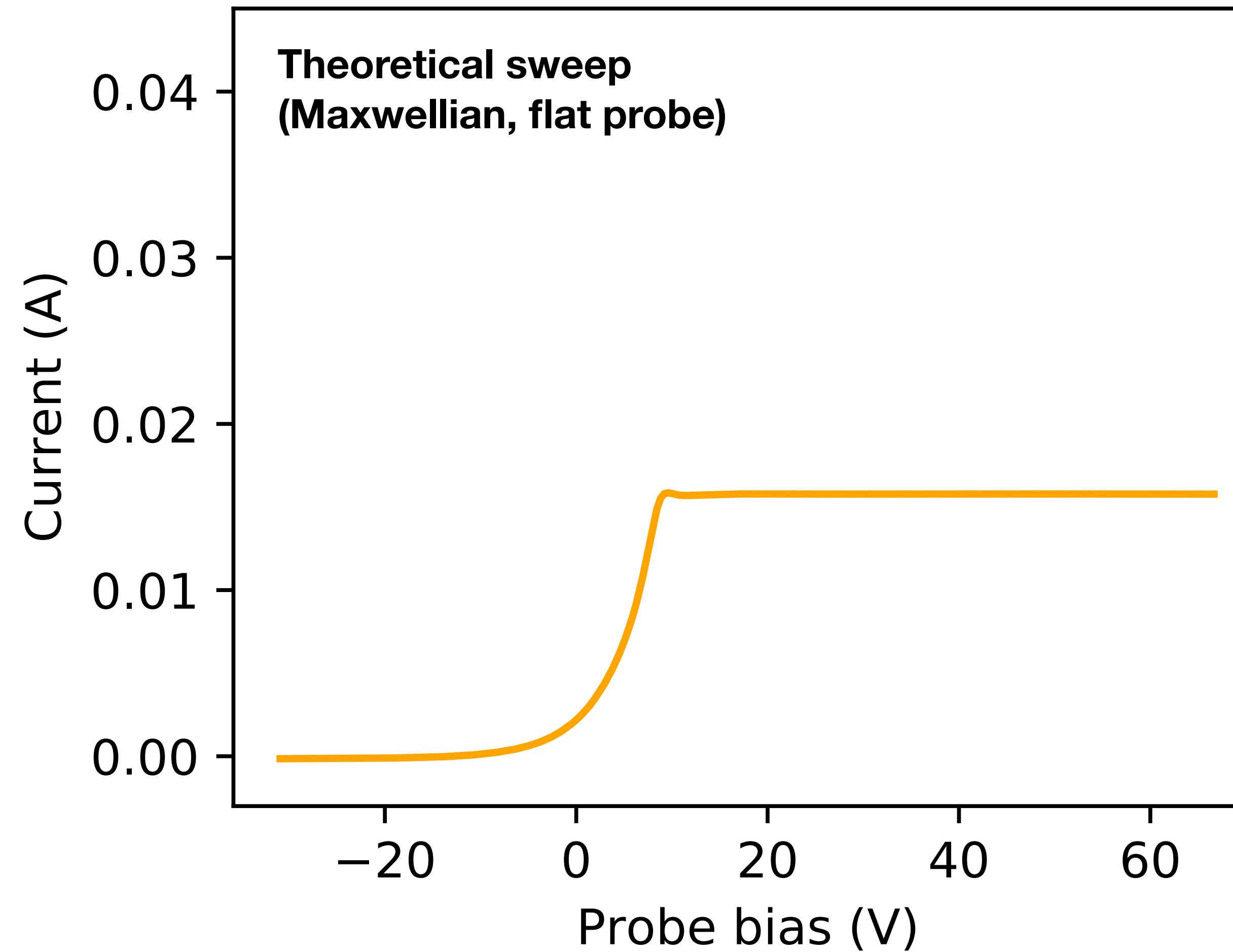
  
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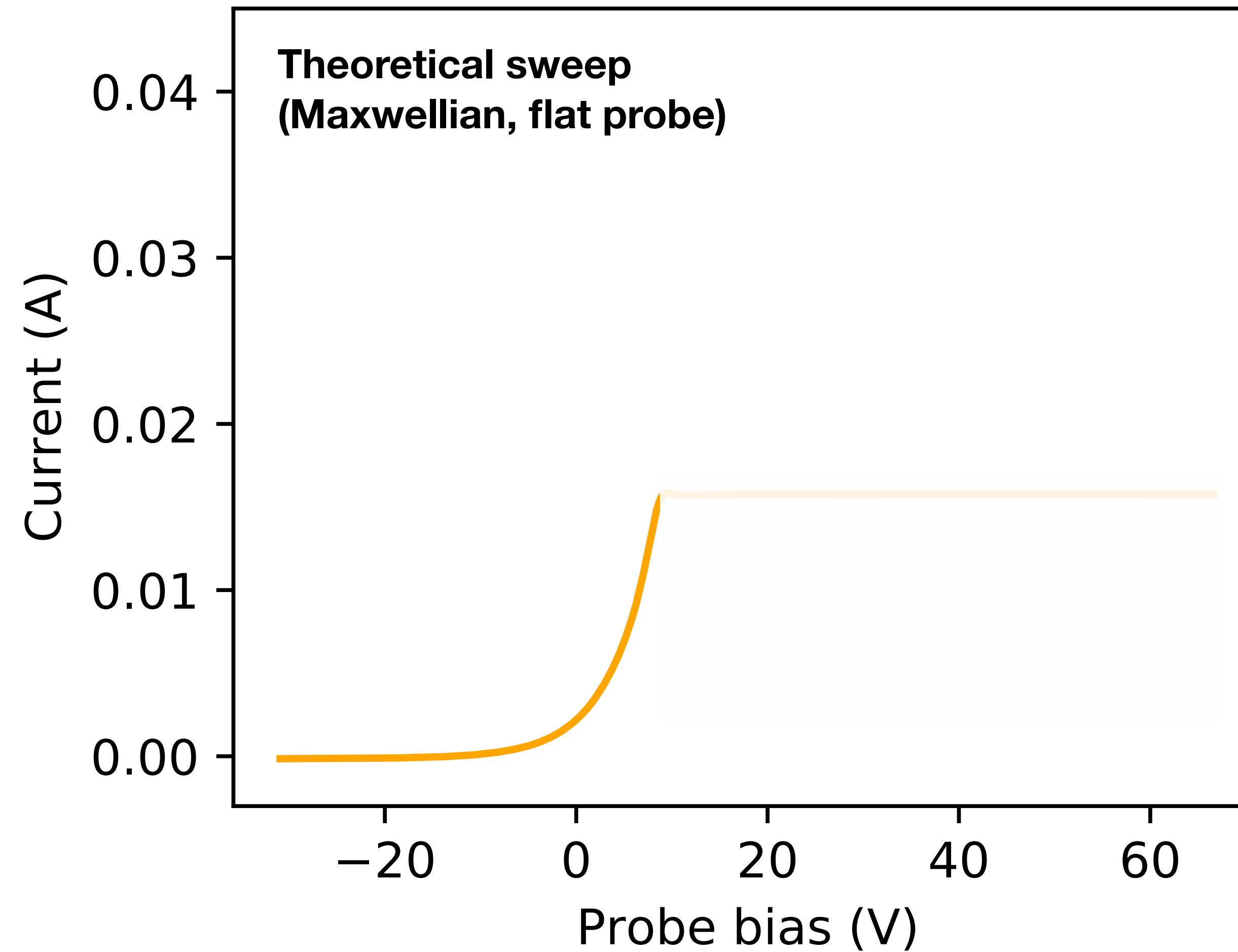


- We can measure temperature, plasma potential (but density is hard to get from esat)

# Theoretically, sweeps are simple



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$$I(V_B) = A_{eff} n_e e \sqrt{\frac{T_e}{2\pi m_e}} e^{-\frac{e(V_p - V_B)}{T_e}}, V_b < V_p$$

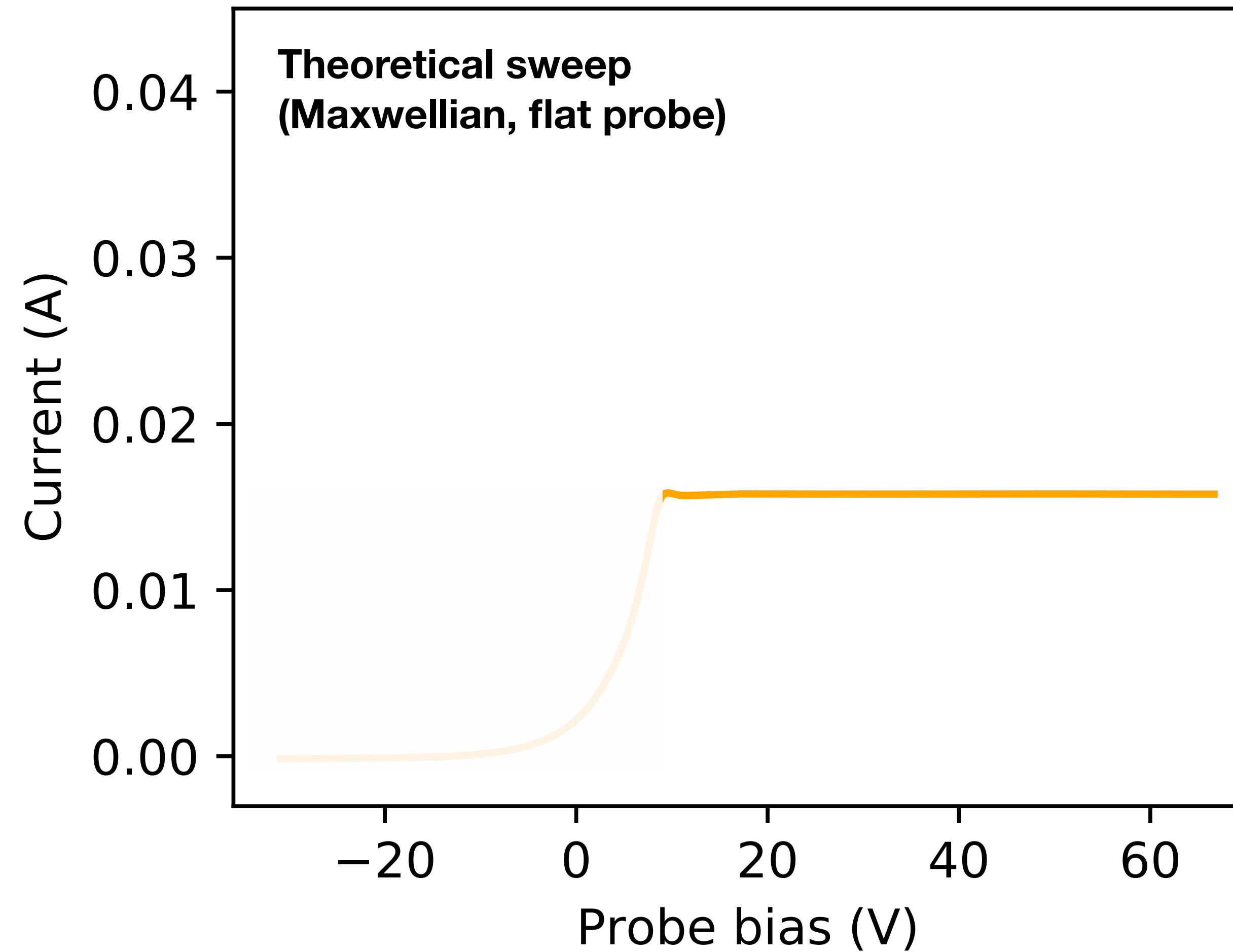
Plasma potential

Probe bias

Electron density

Electron temperature

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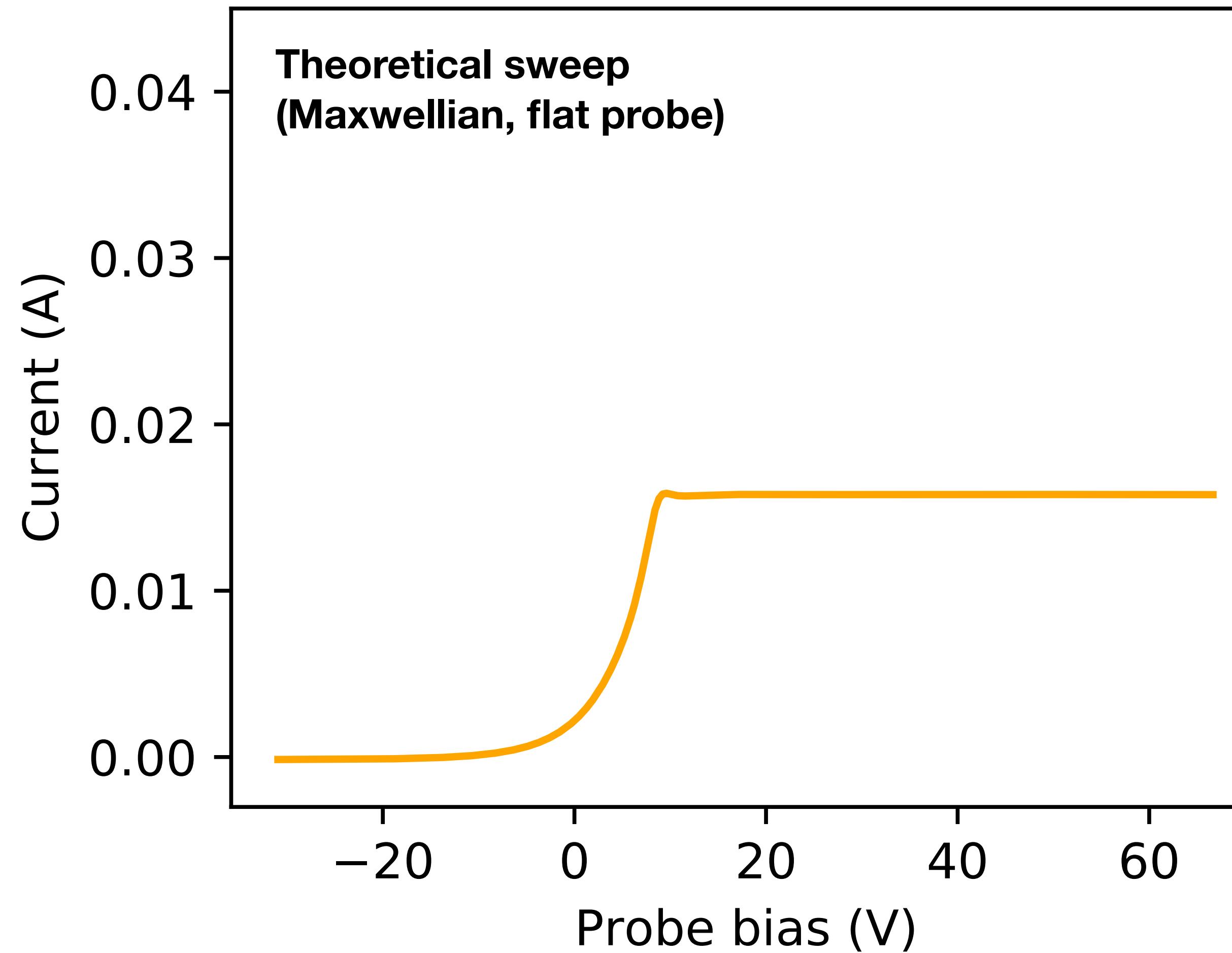
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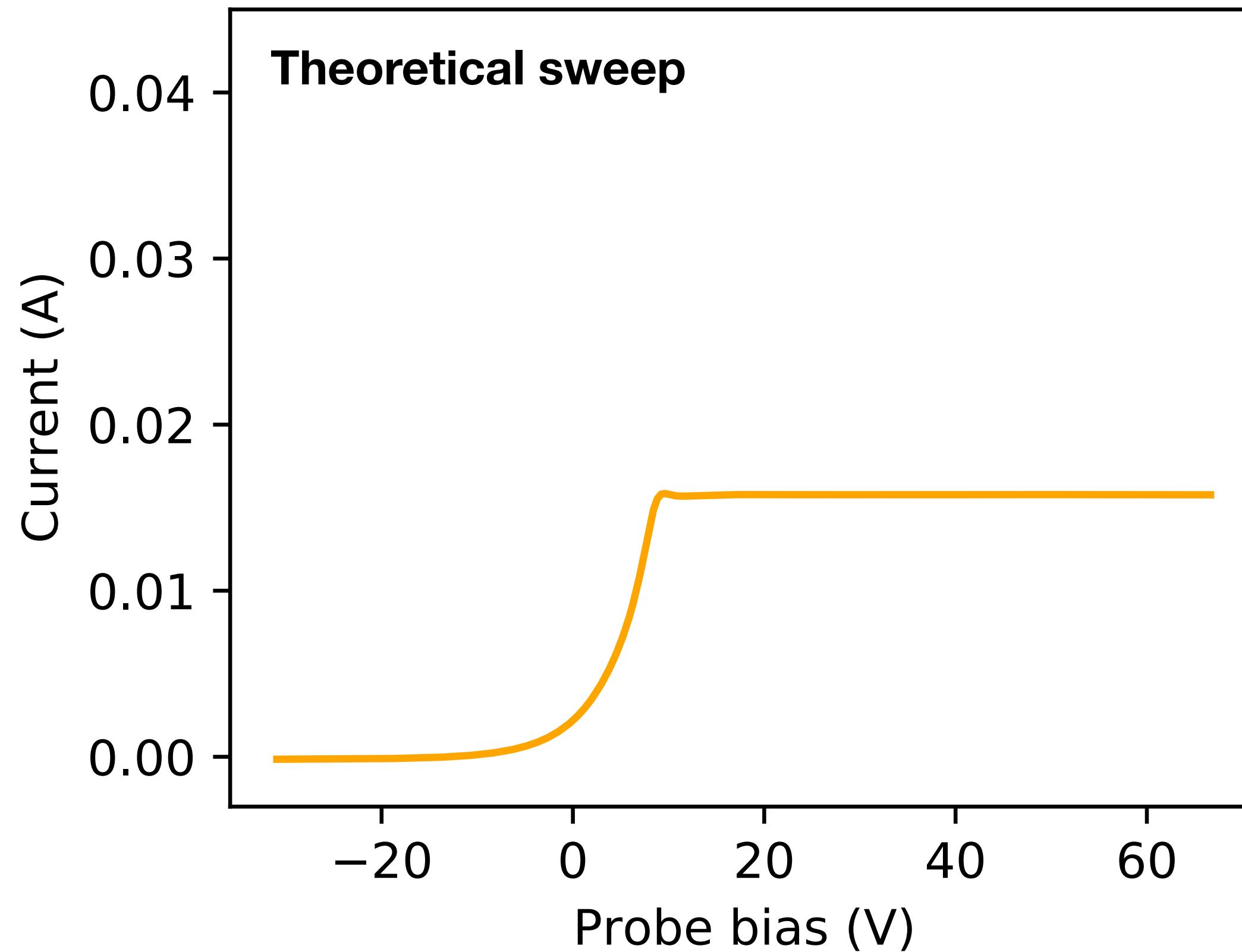
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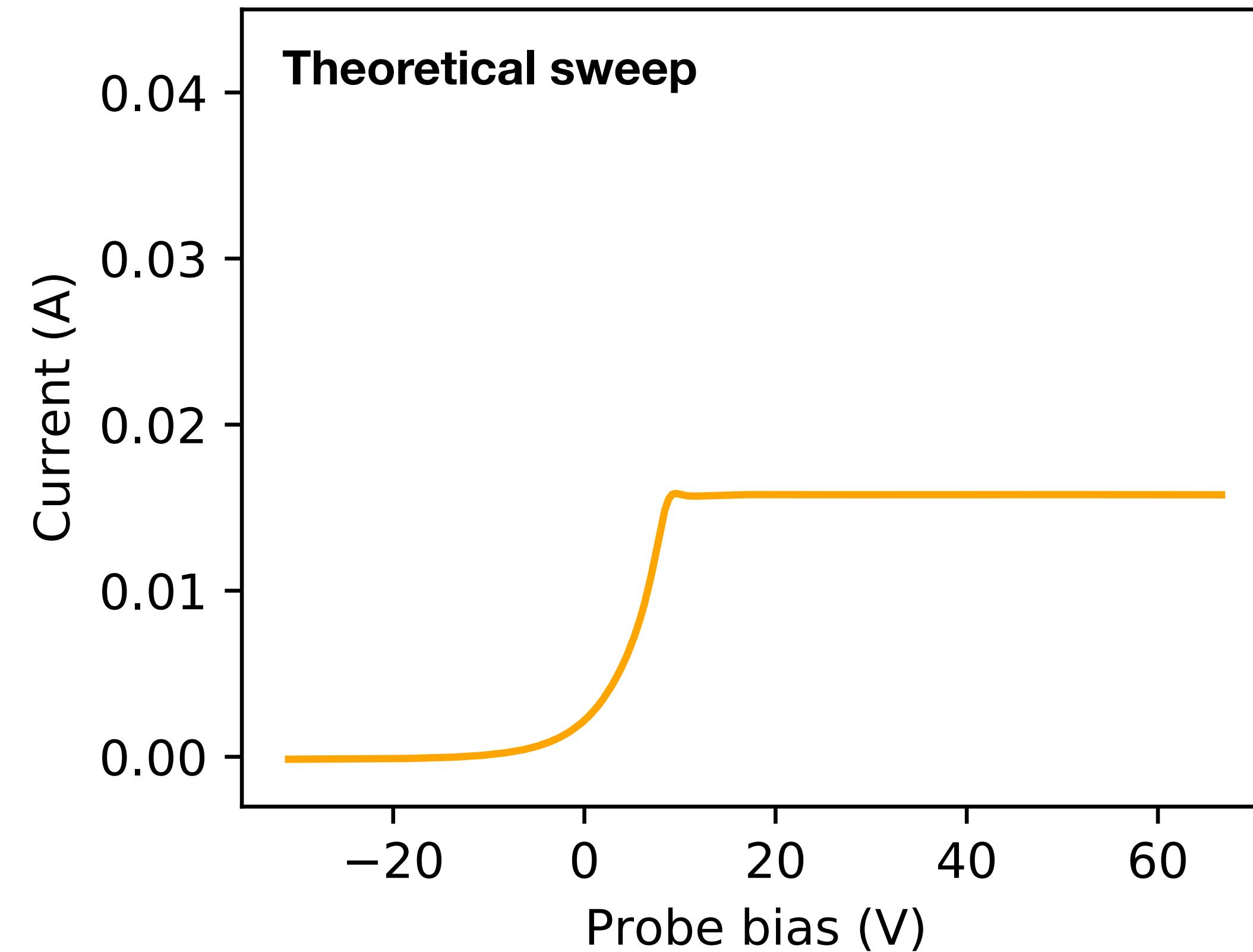
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# Real sweeps can be gnarly, dude

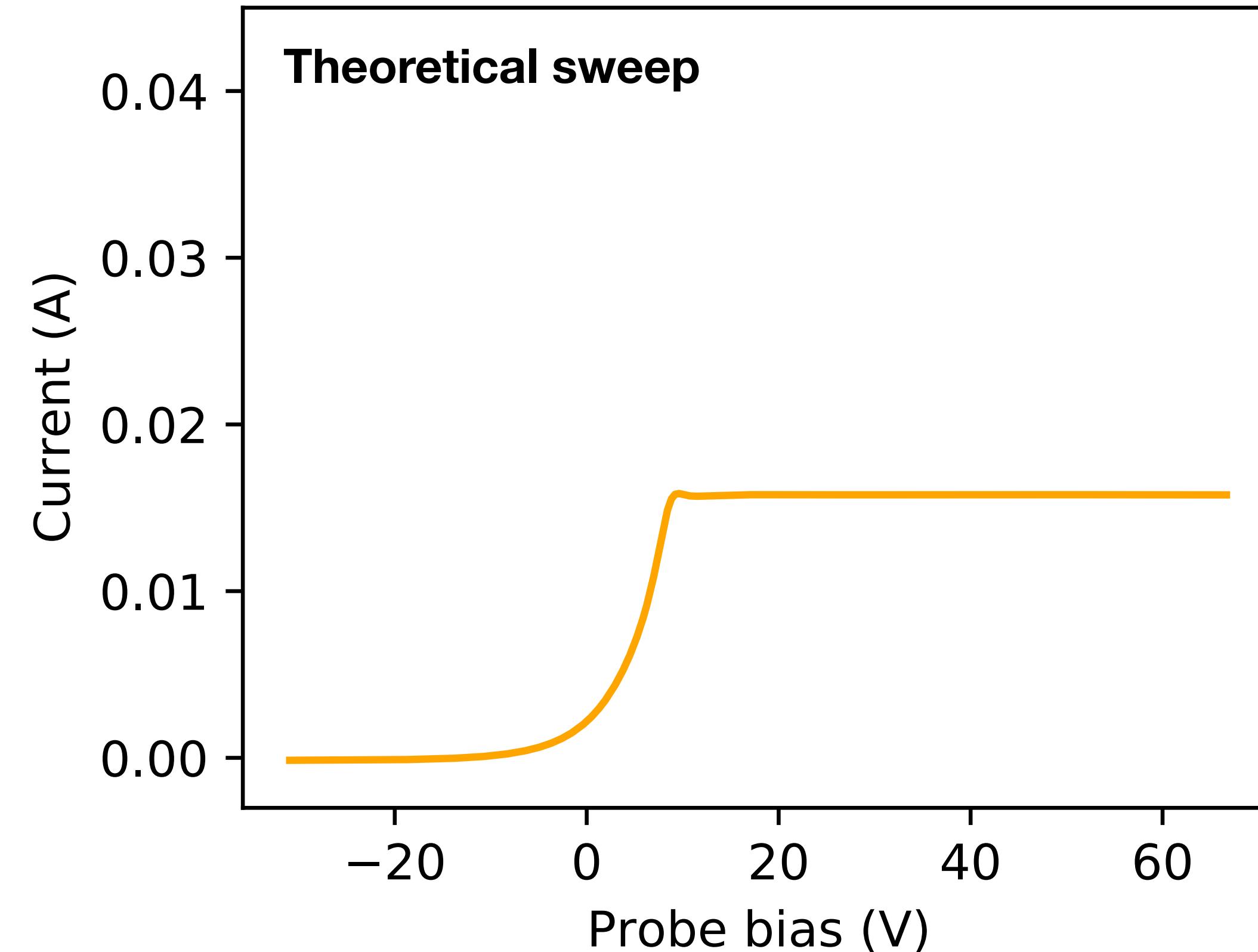
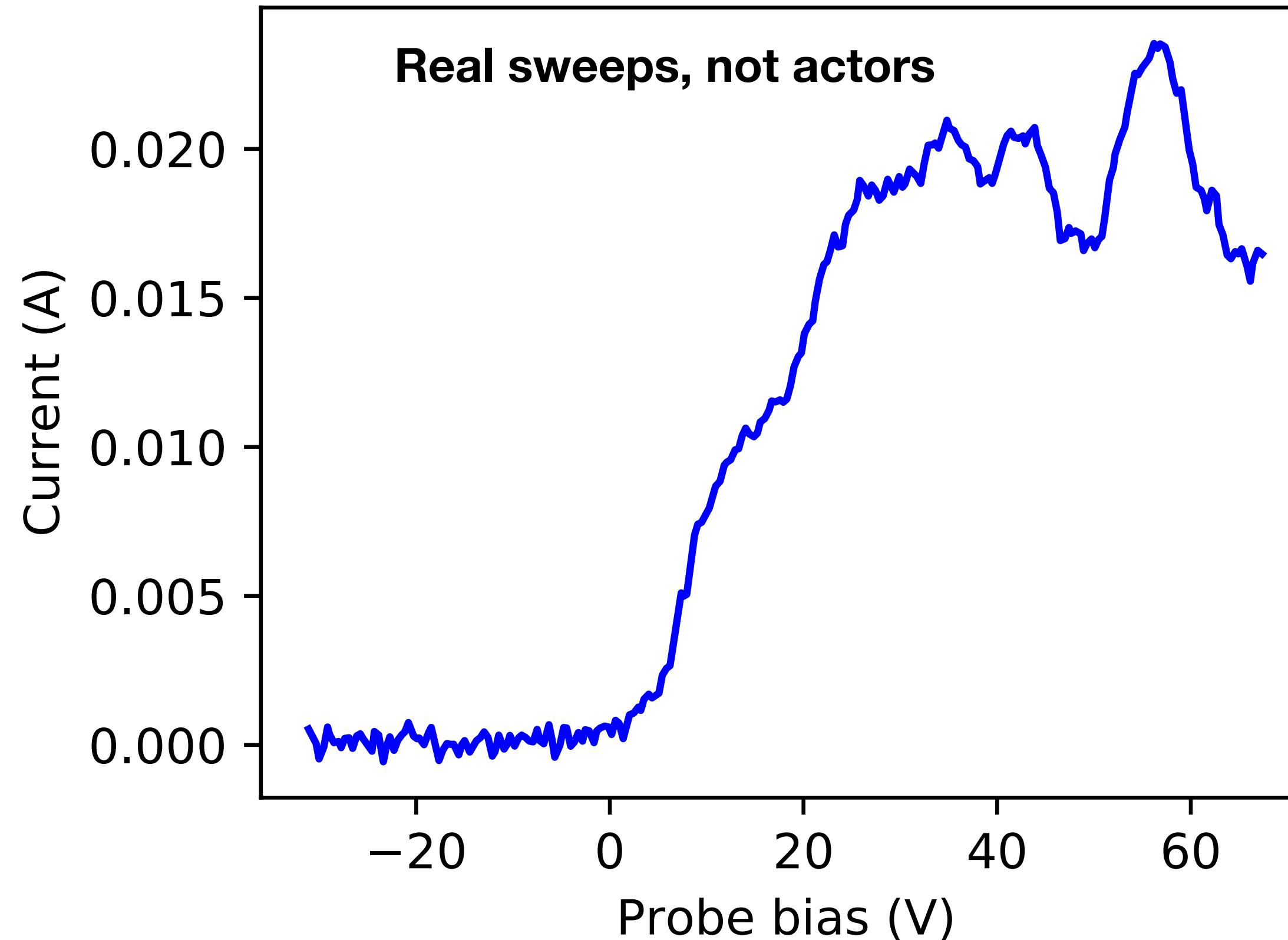


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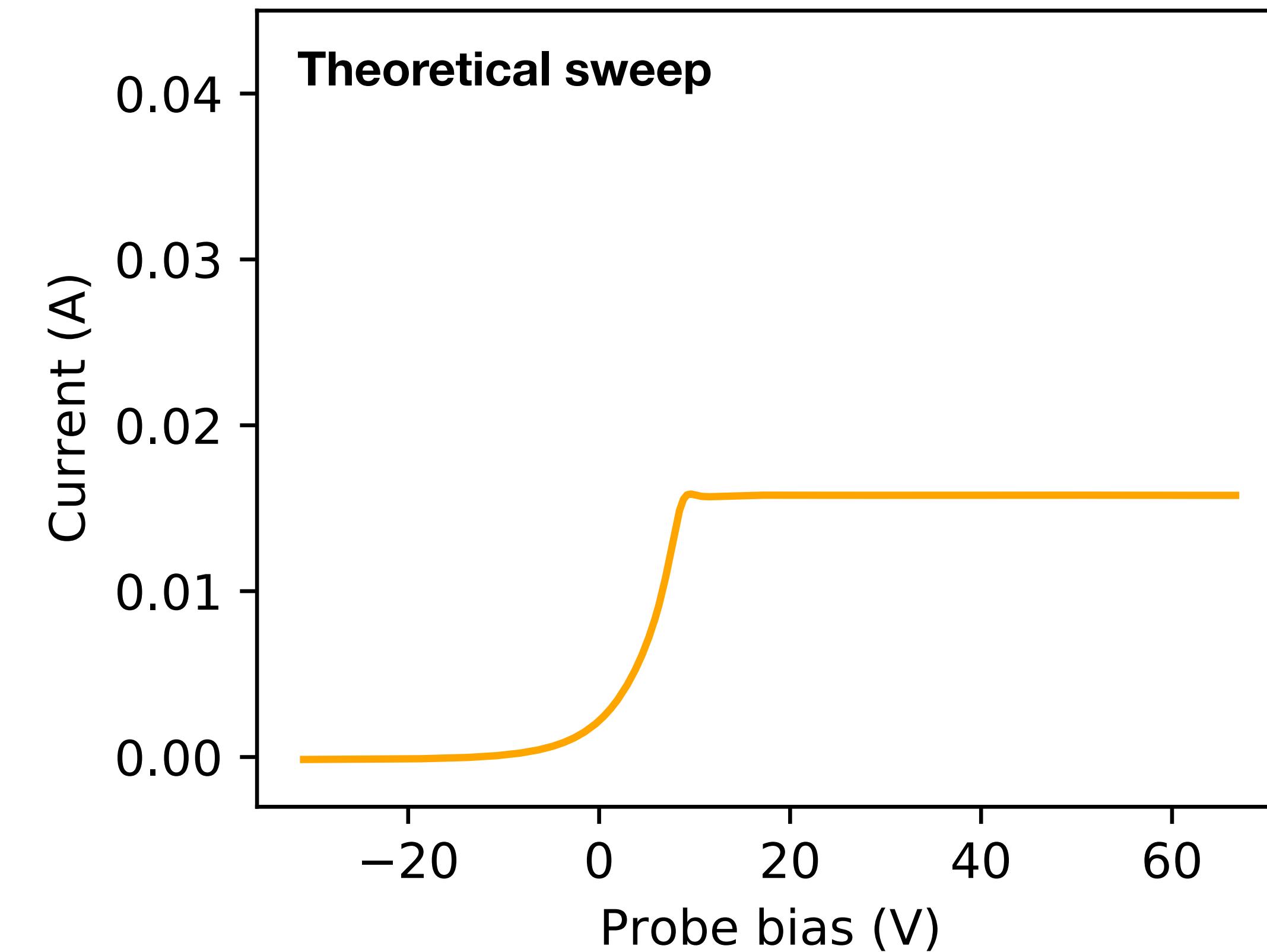
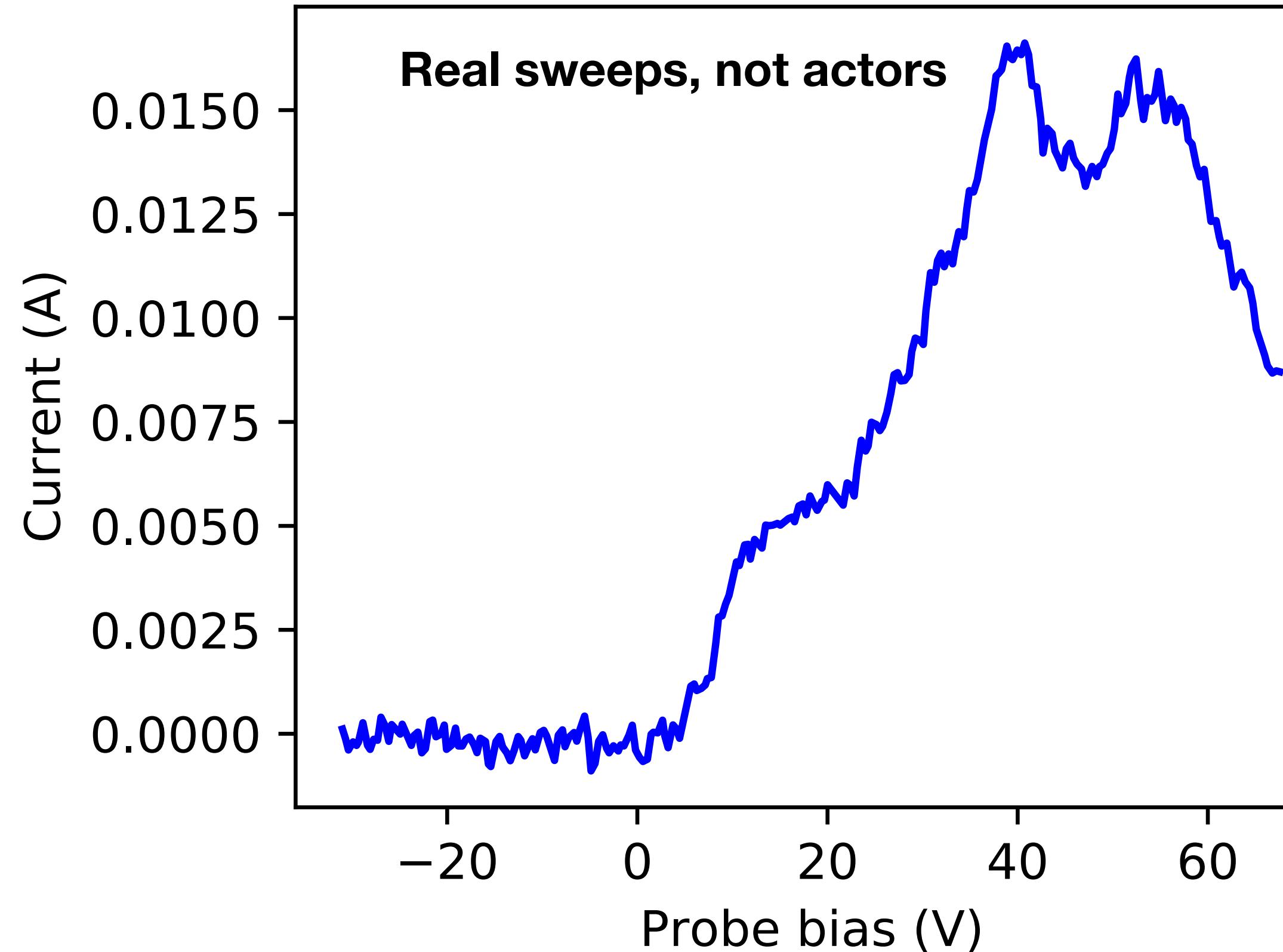
Real sweeps, not actors



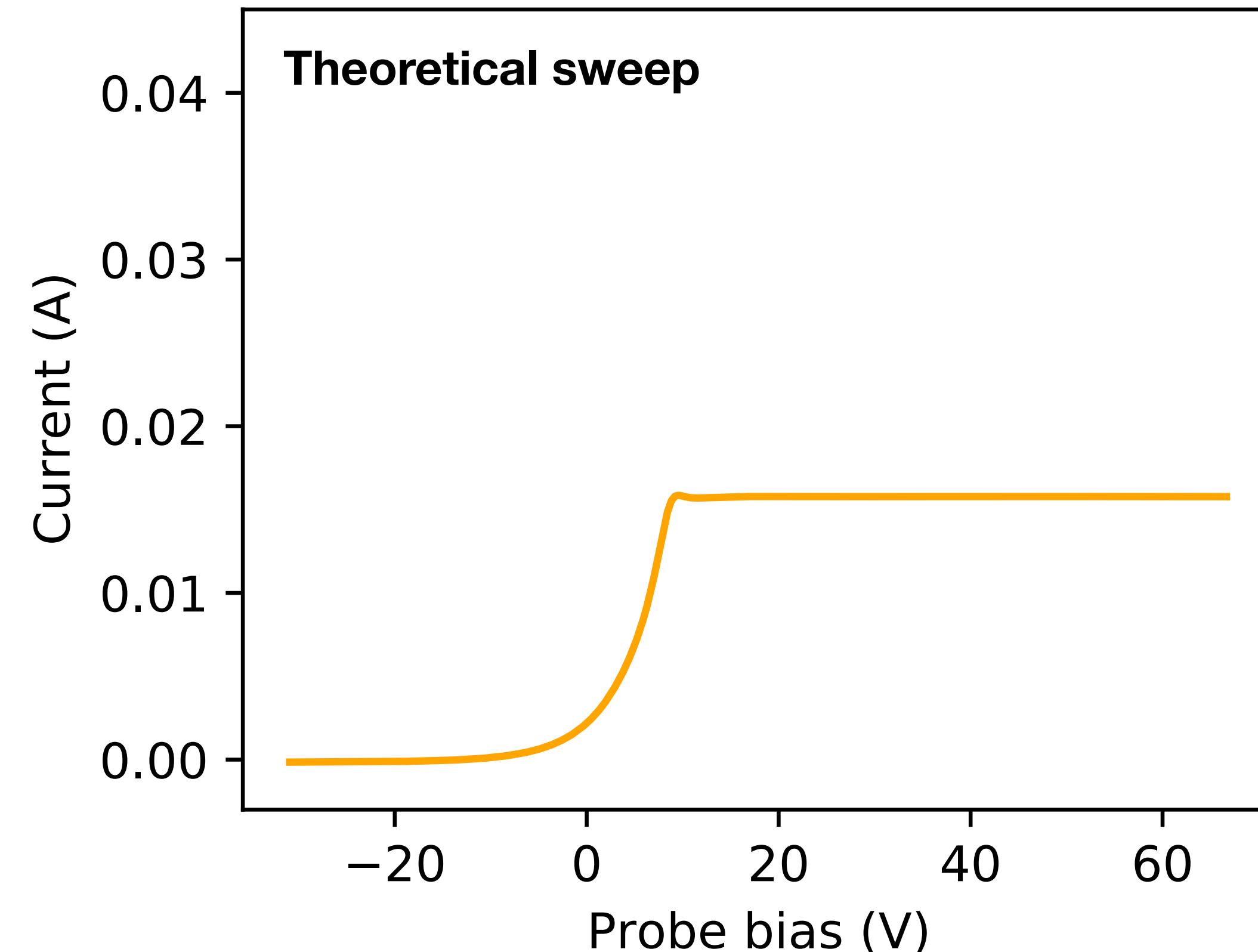
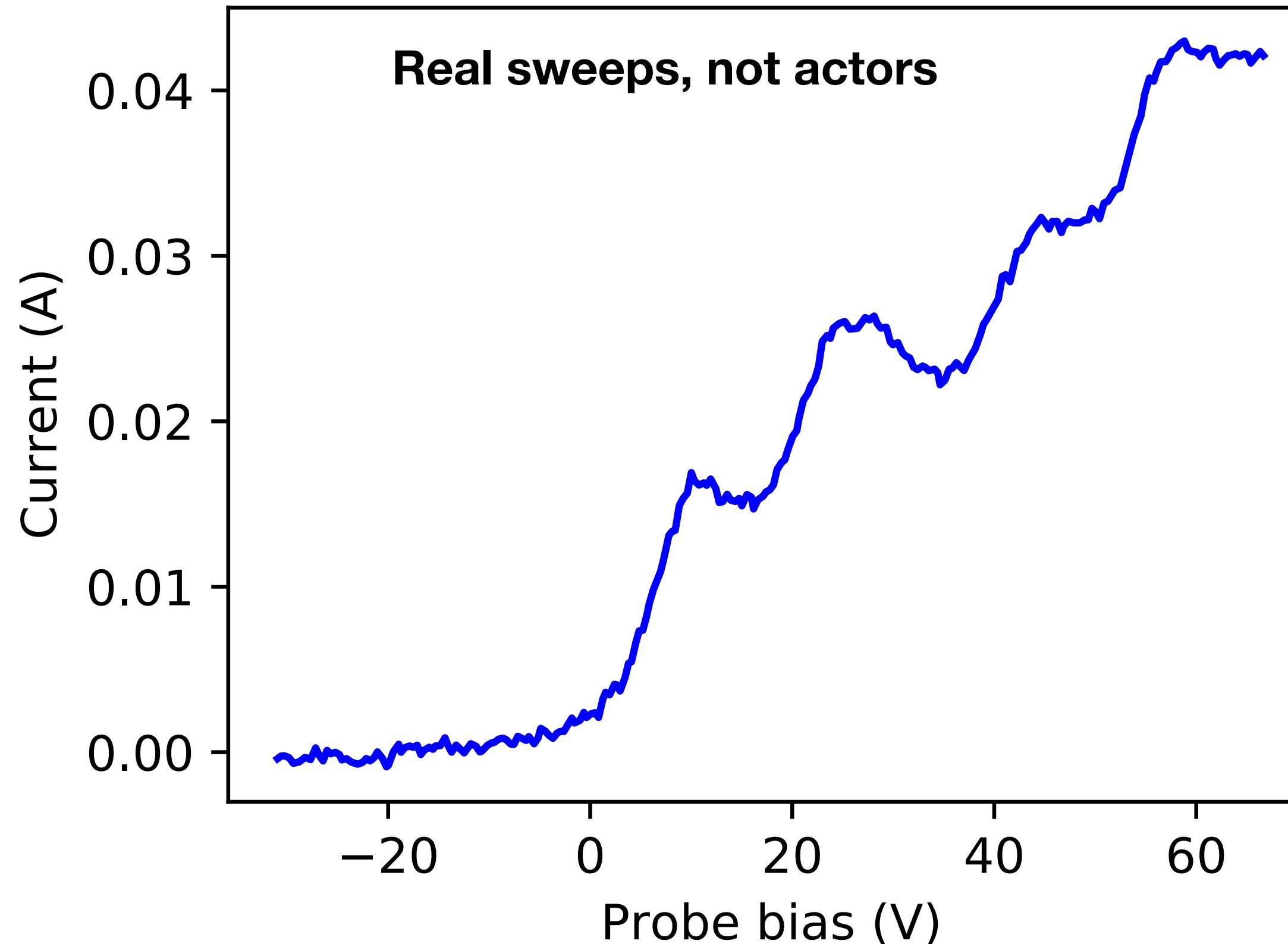
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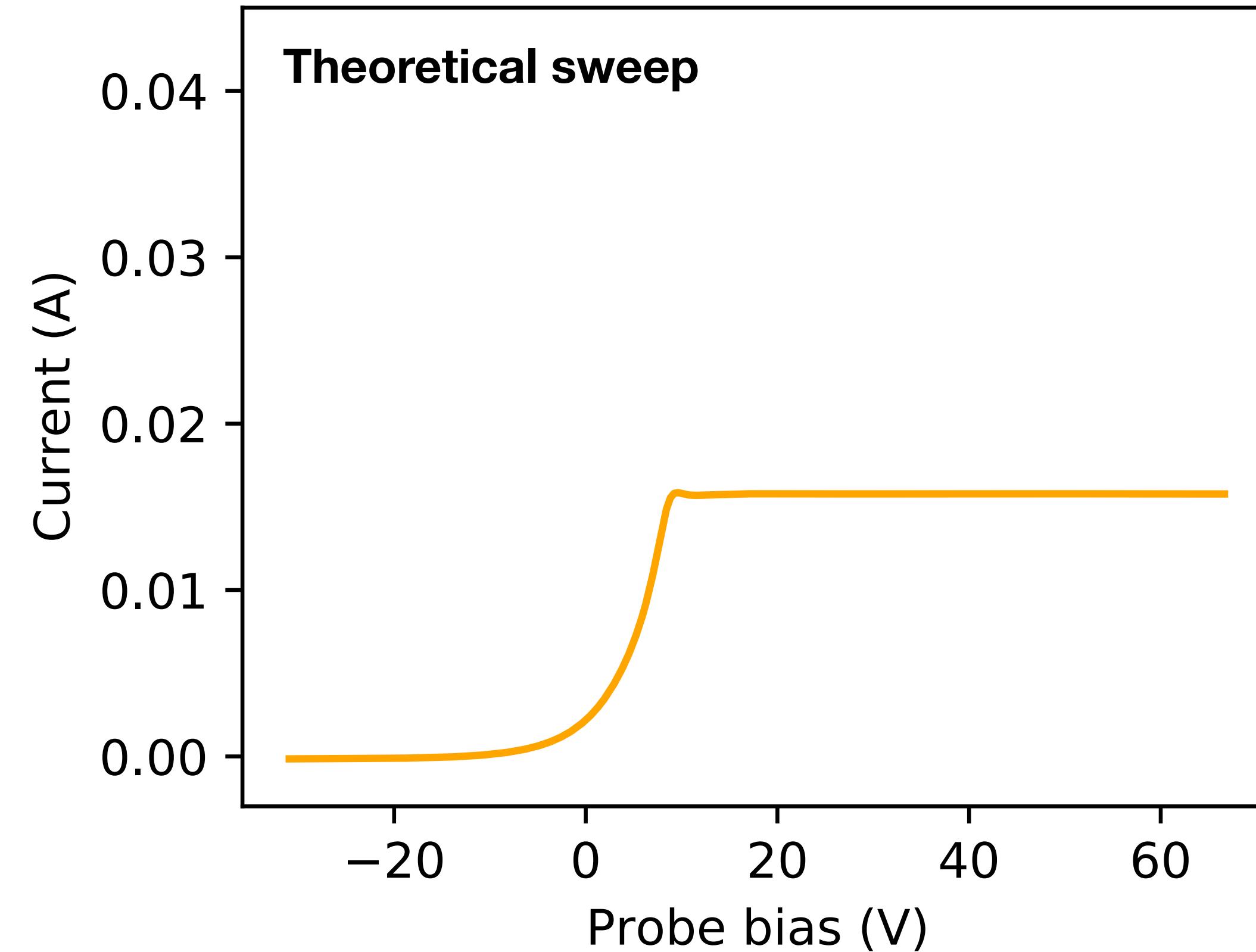
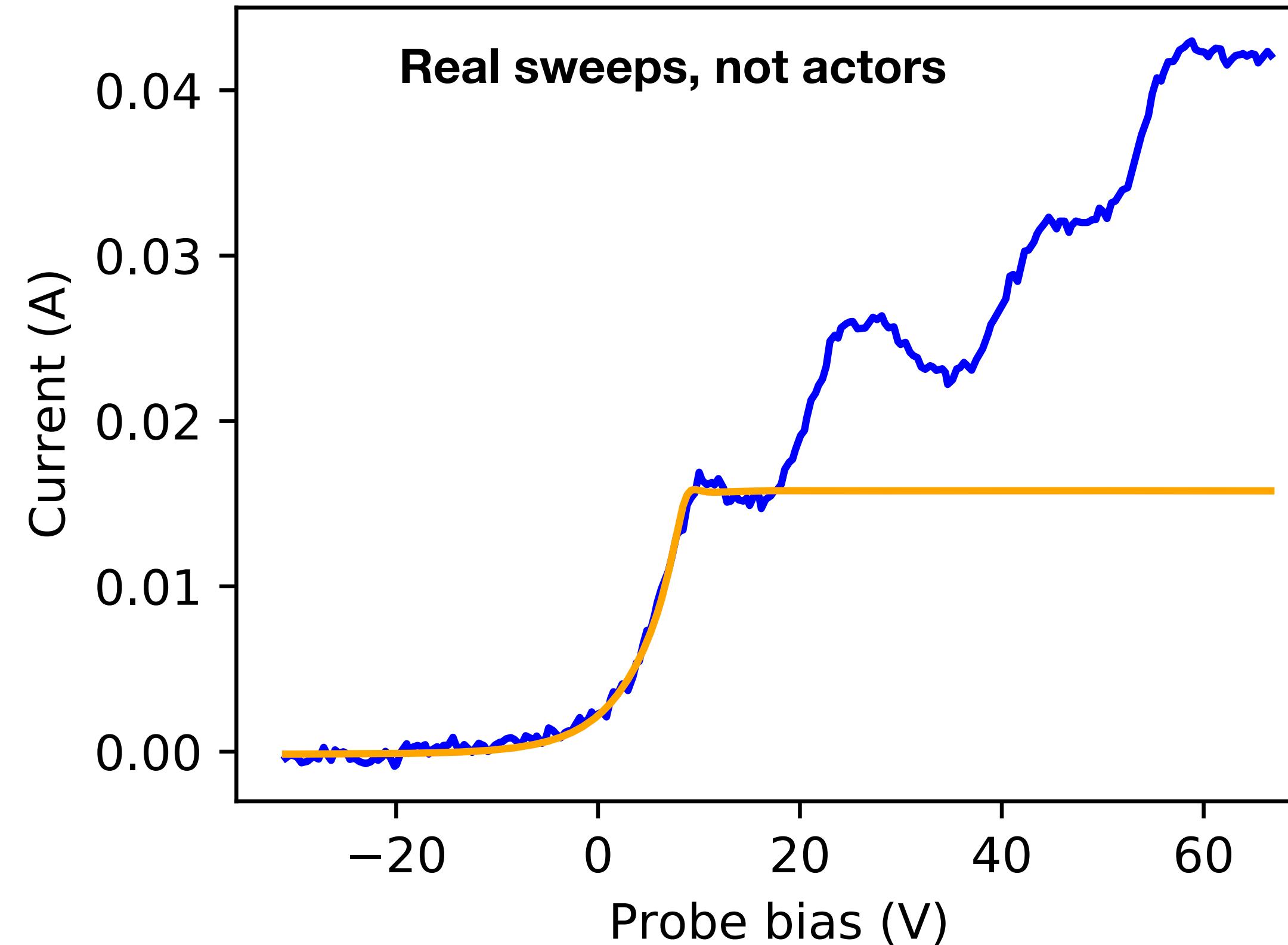
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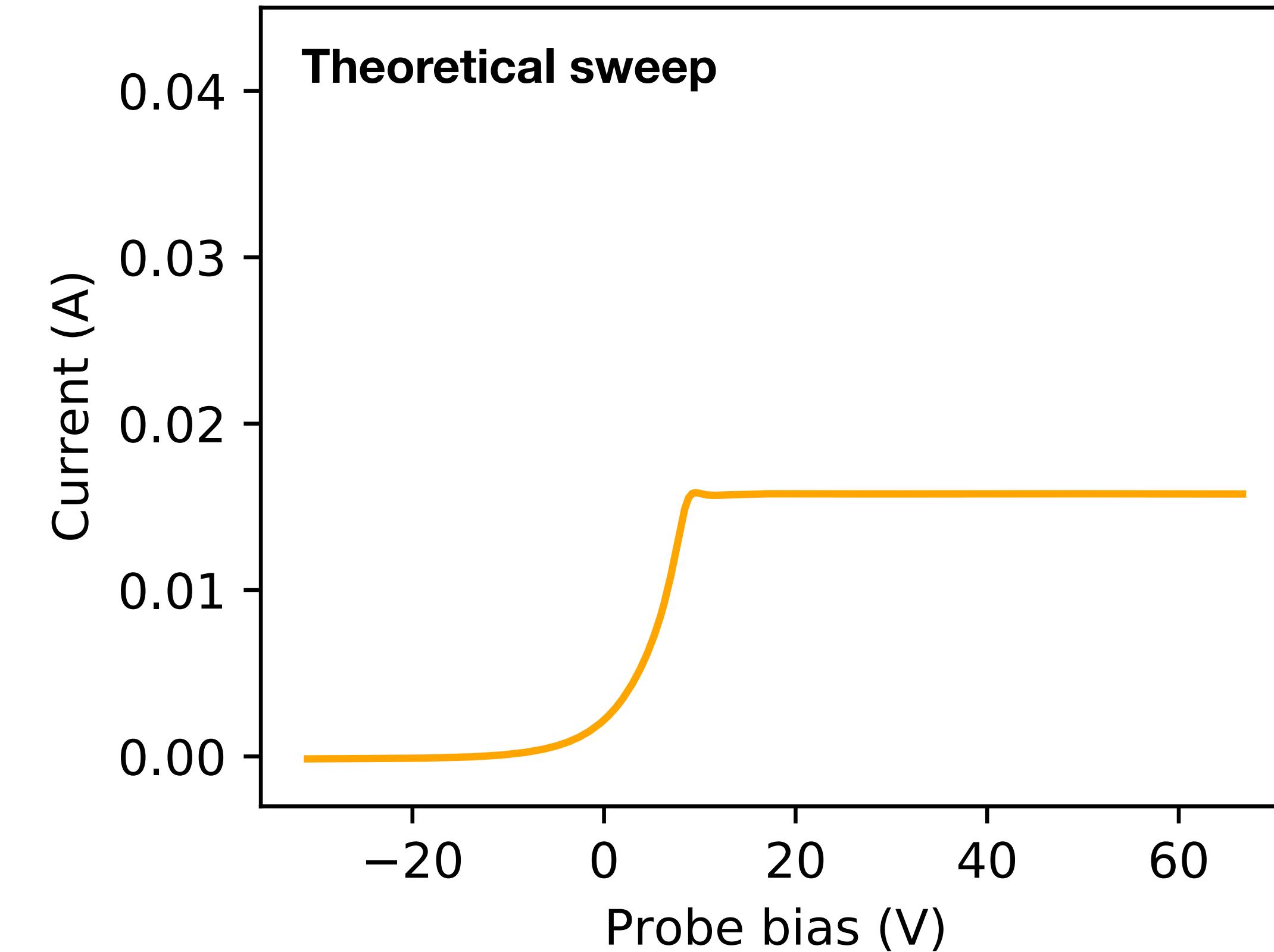
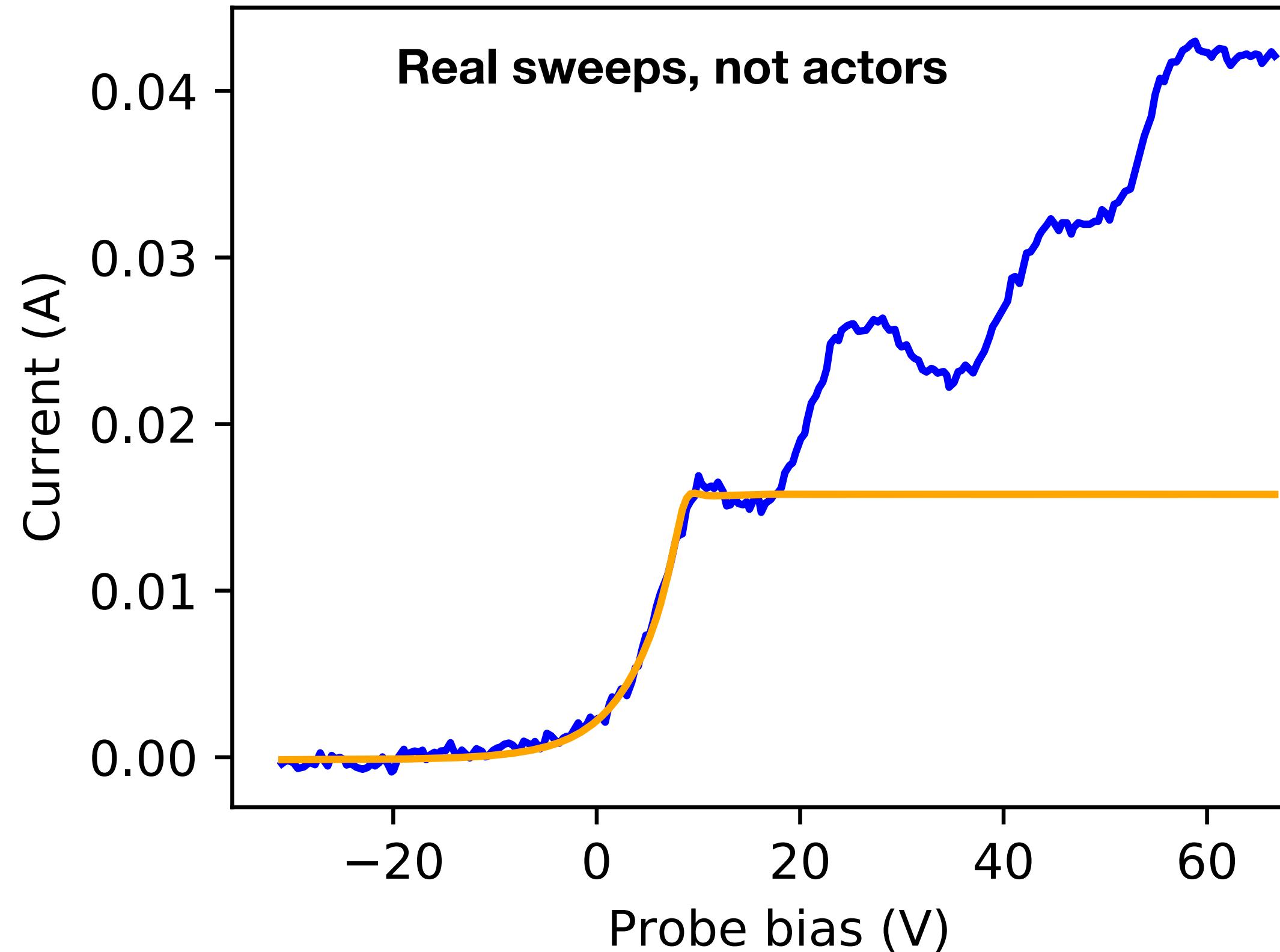
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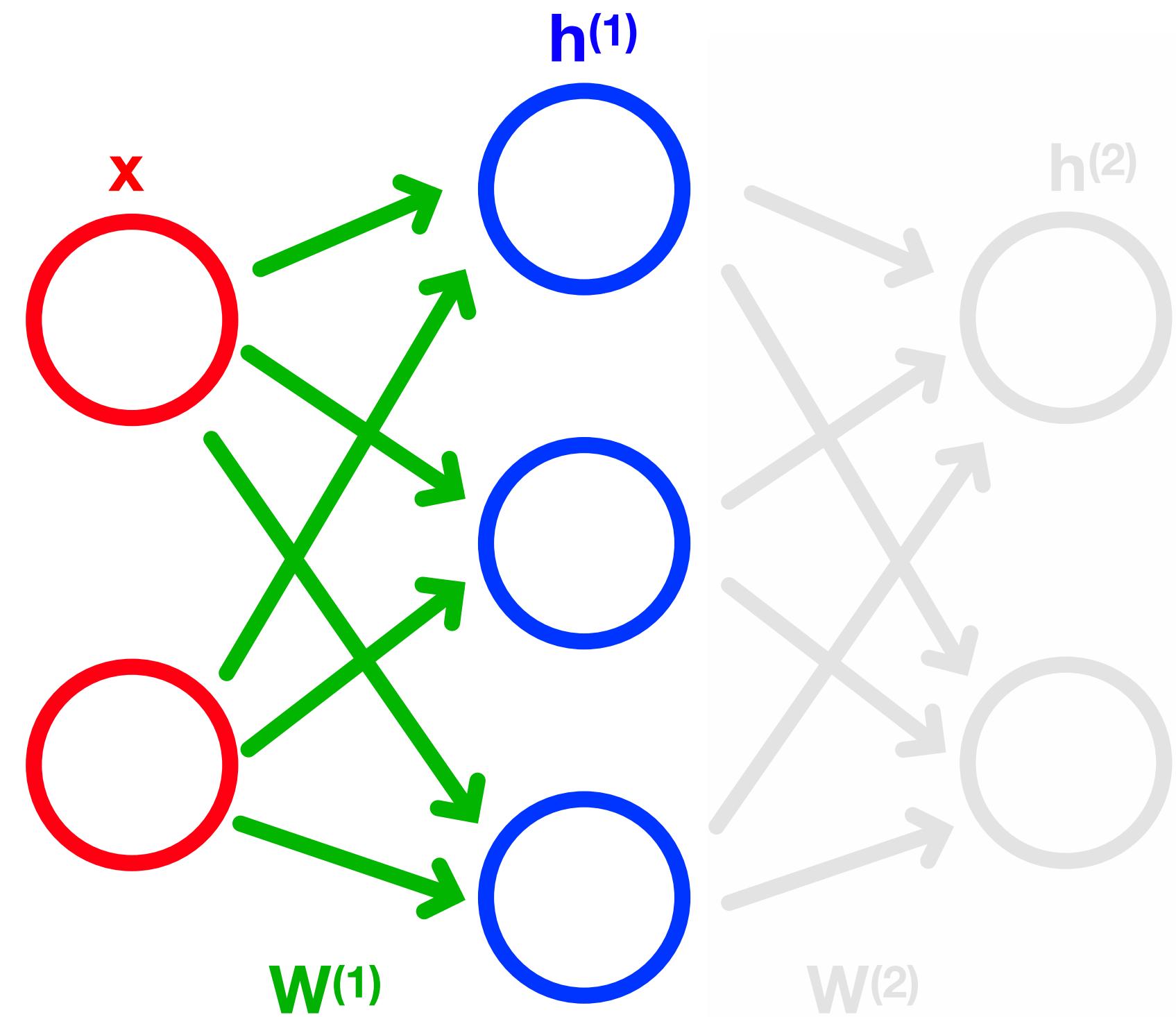


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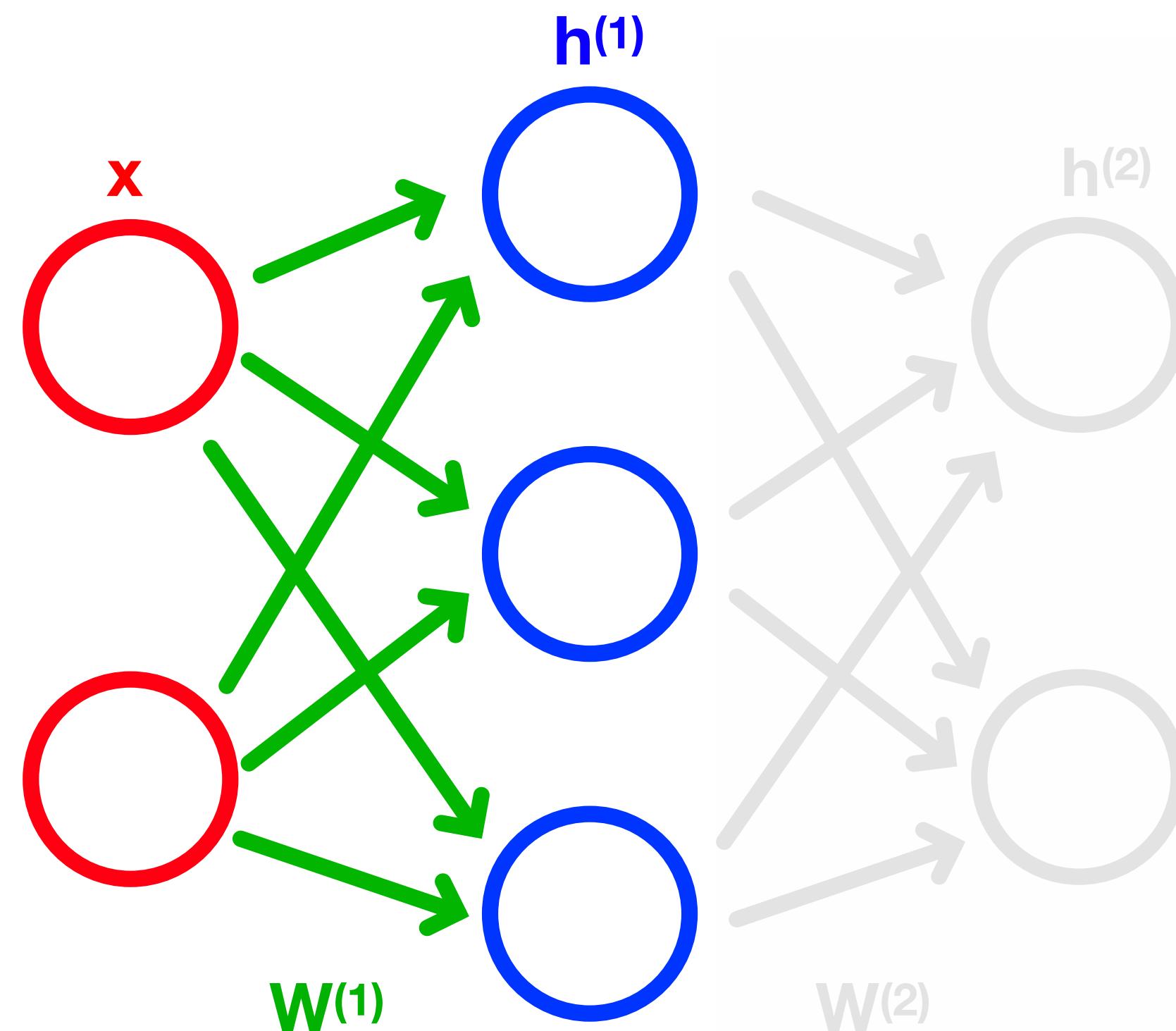


- Lots of turbulence / fluctuations past 25 cm
- Routines that work for one parameter range will break for others

# Performing this fitting task with machine learning (neural nets)



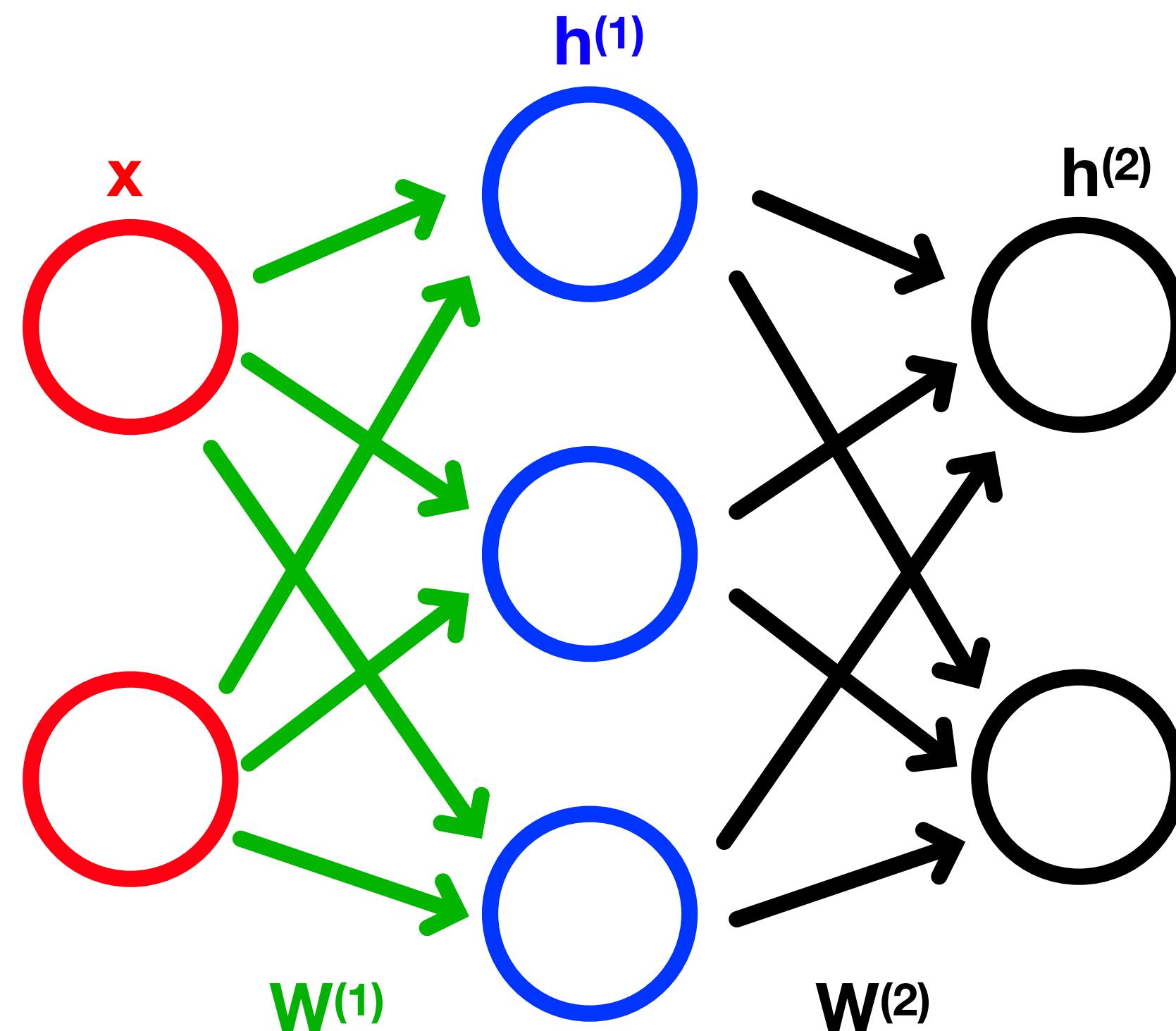
# Performing this fitting task with machine learning (neural nets)



$$h^{(1)} = g^{(1)} (W^{(1)T} x + b^{(1)})$$

activation  
nonlinear function  
weights  
inputs  
bias

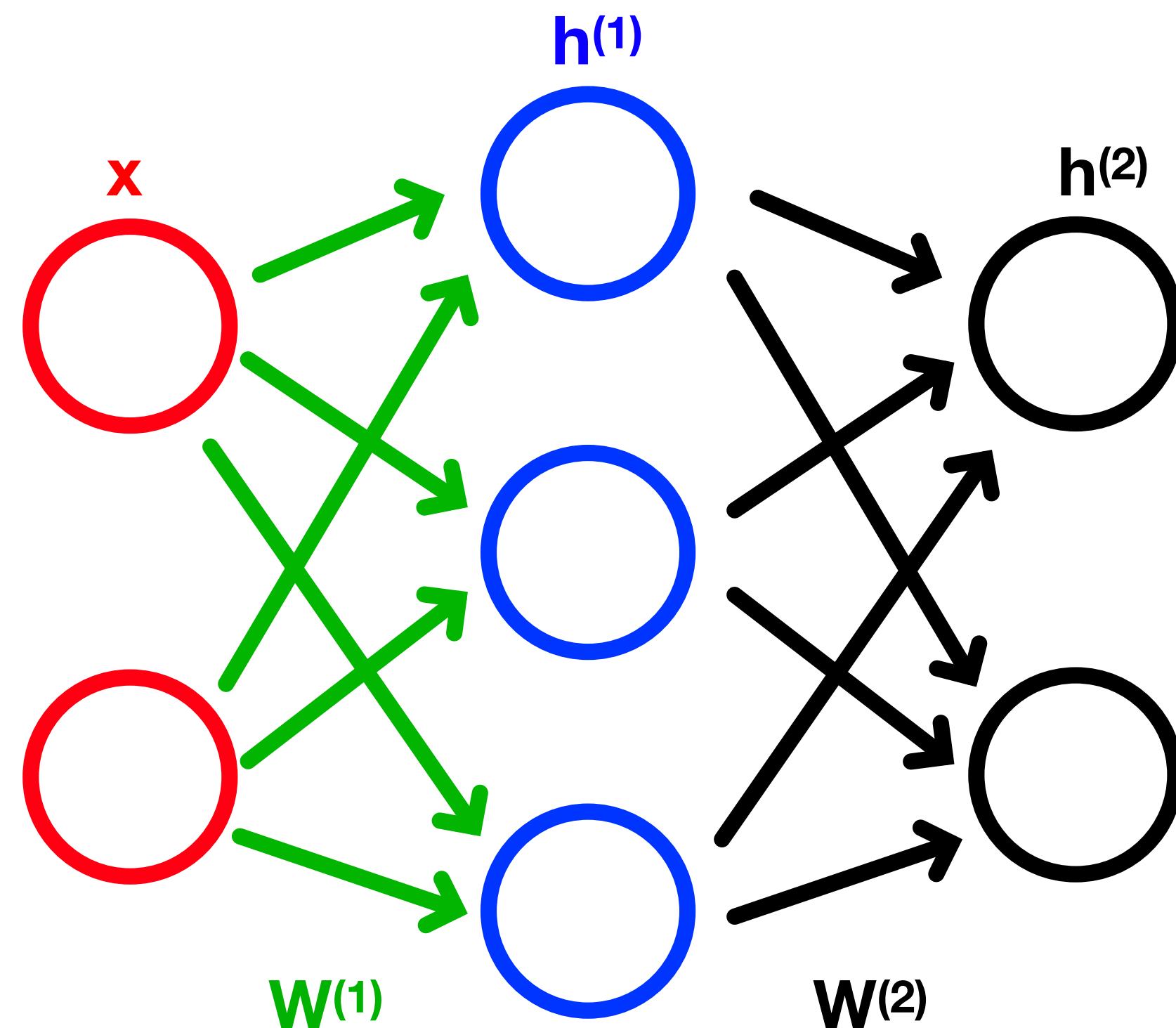
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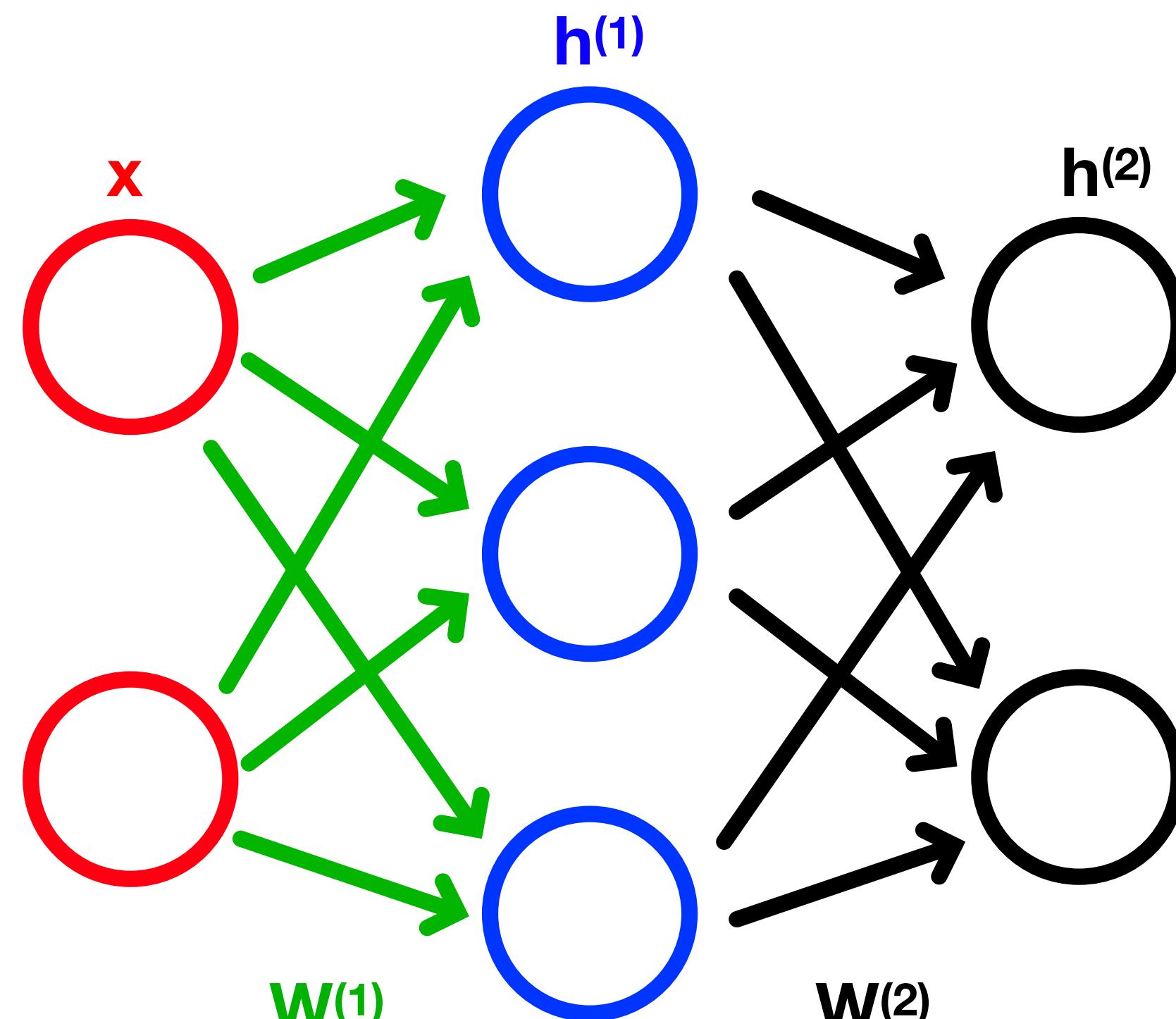


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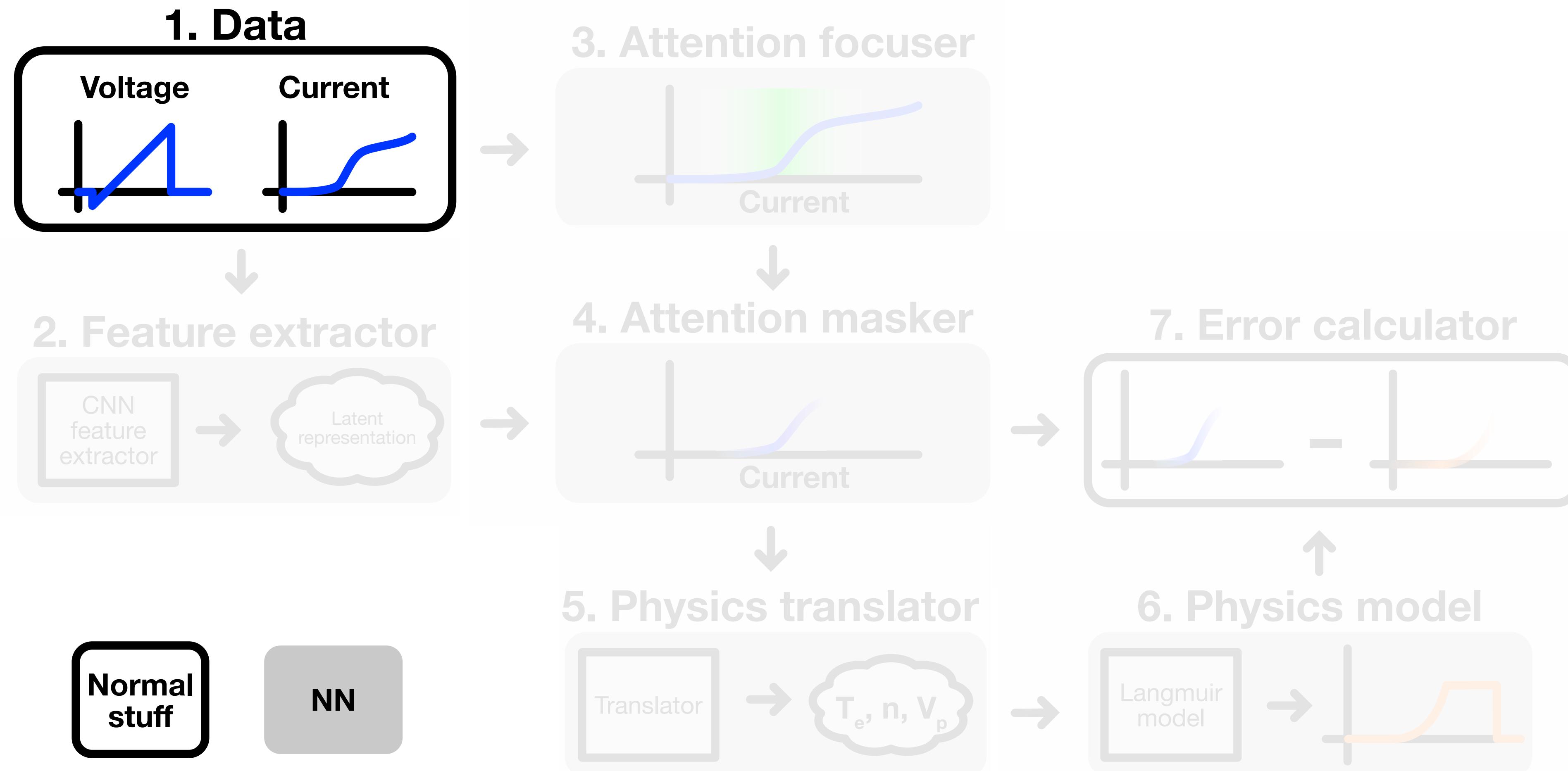
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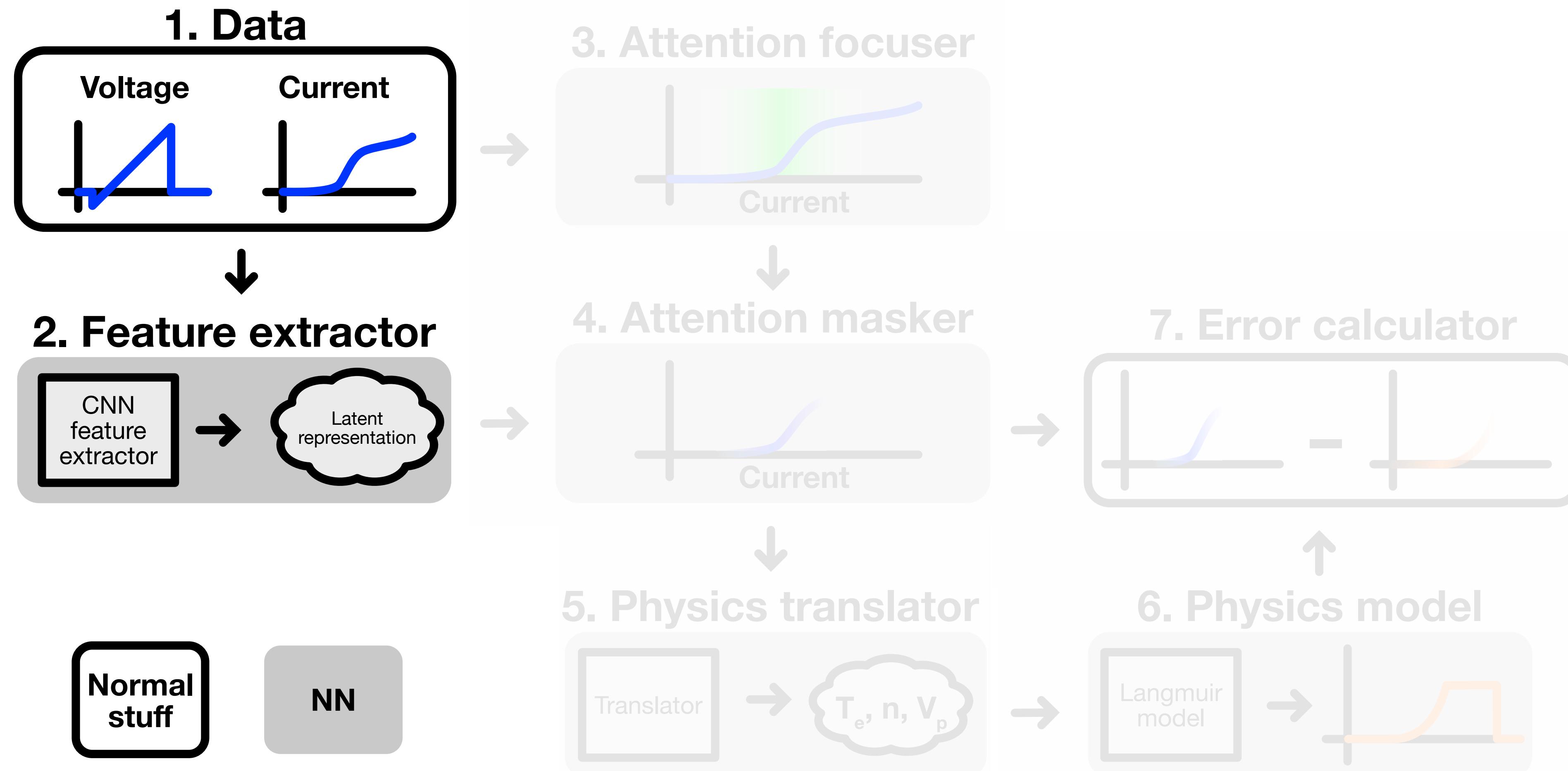
(Deep Learning by Ian Goodfellow)

^ can learn any function

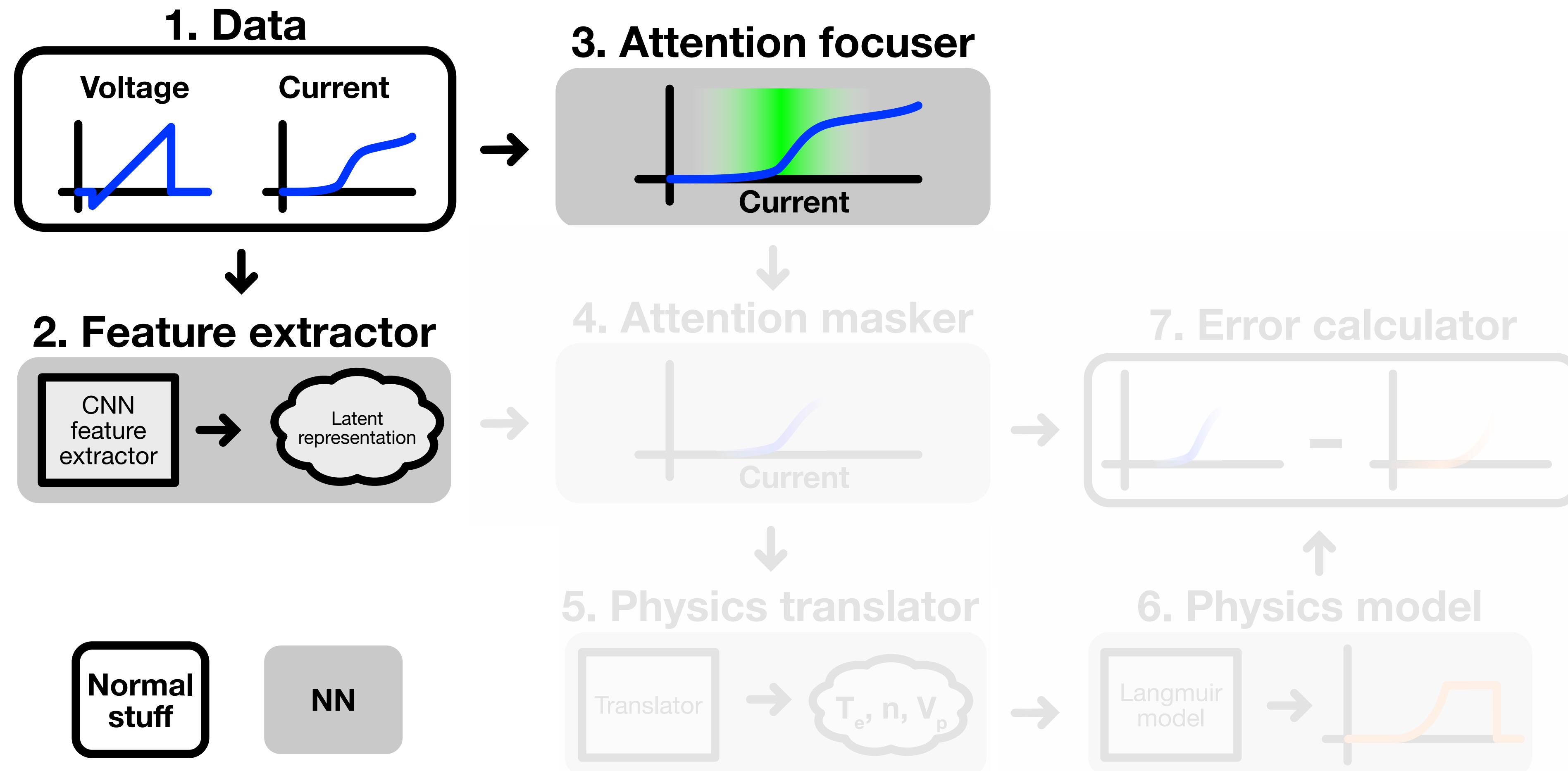
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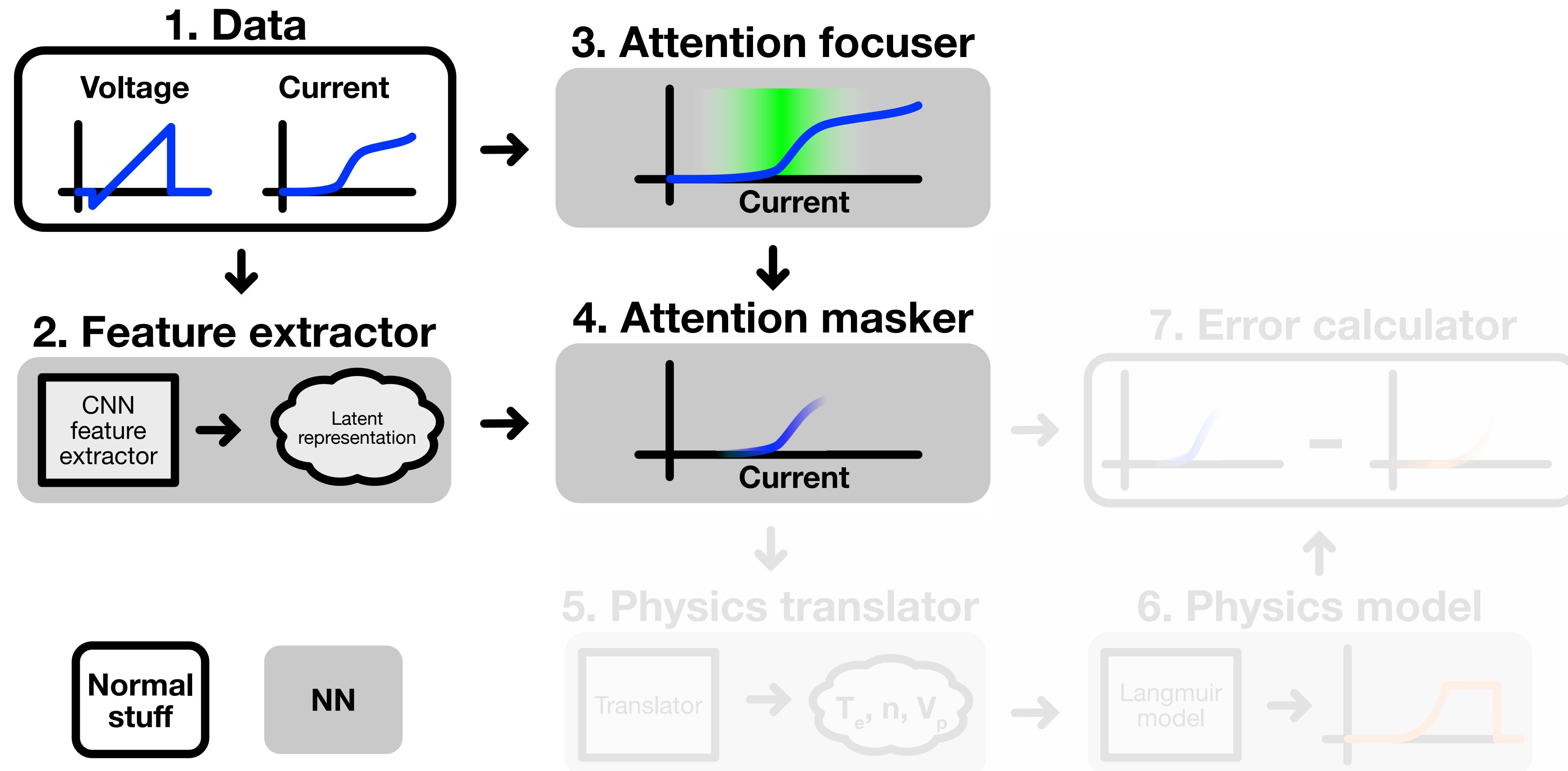
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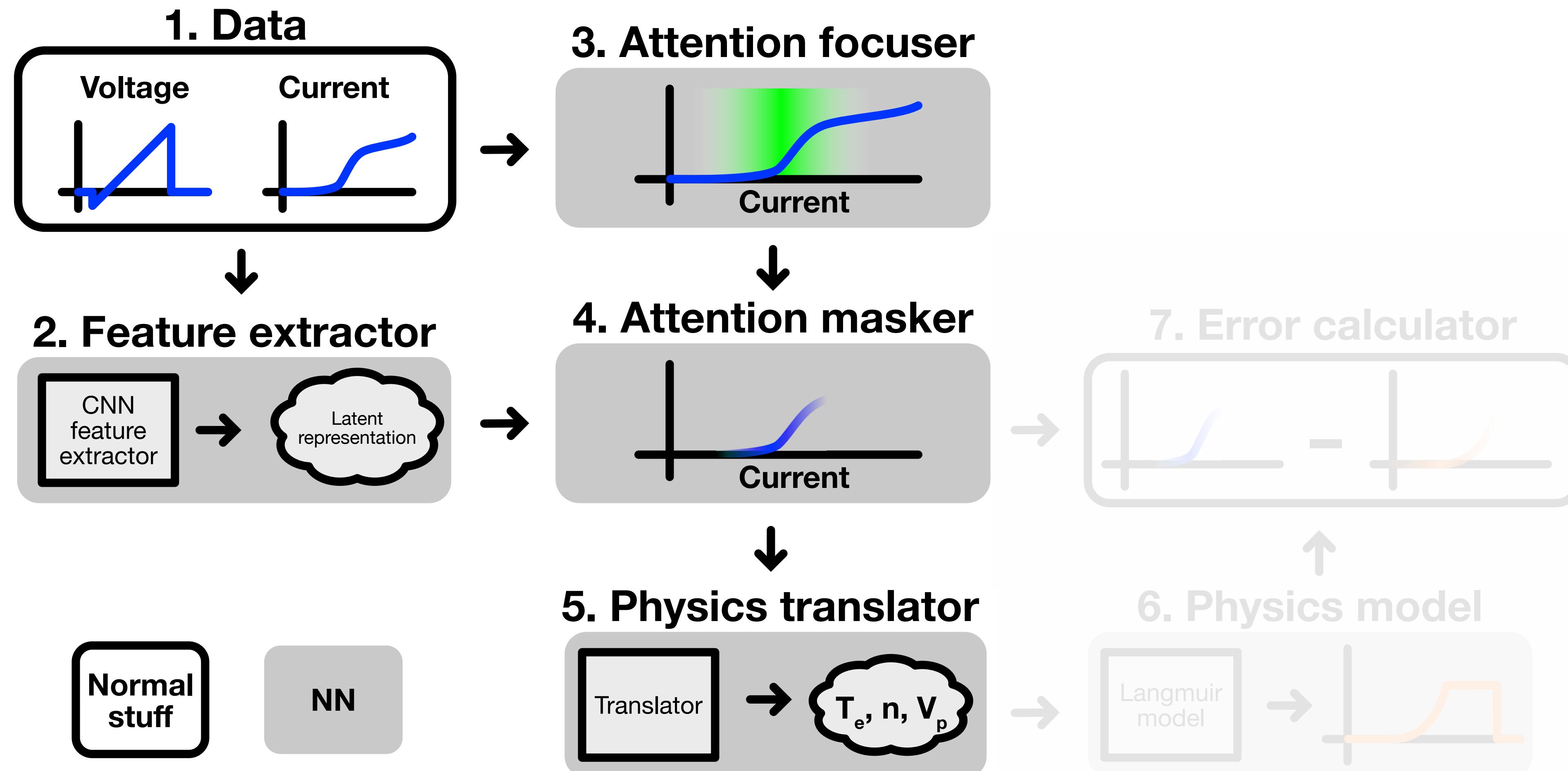
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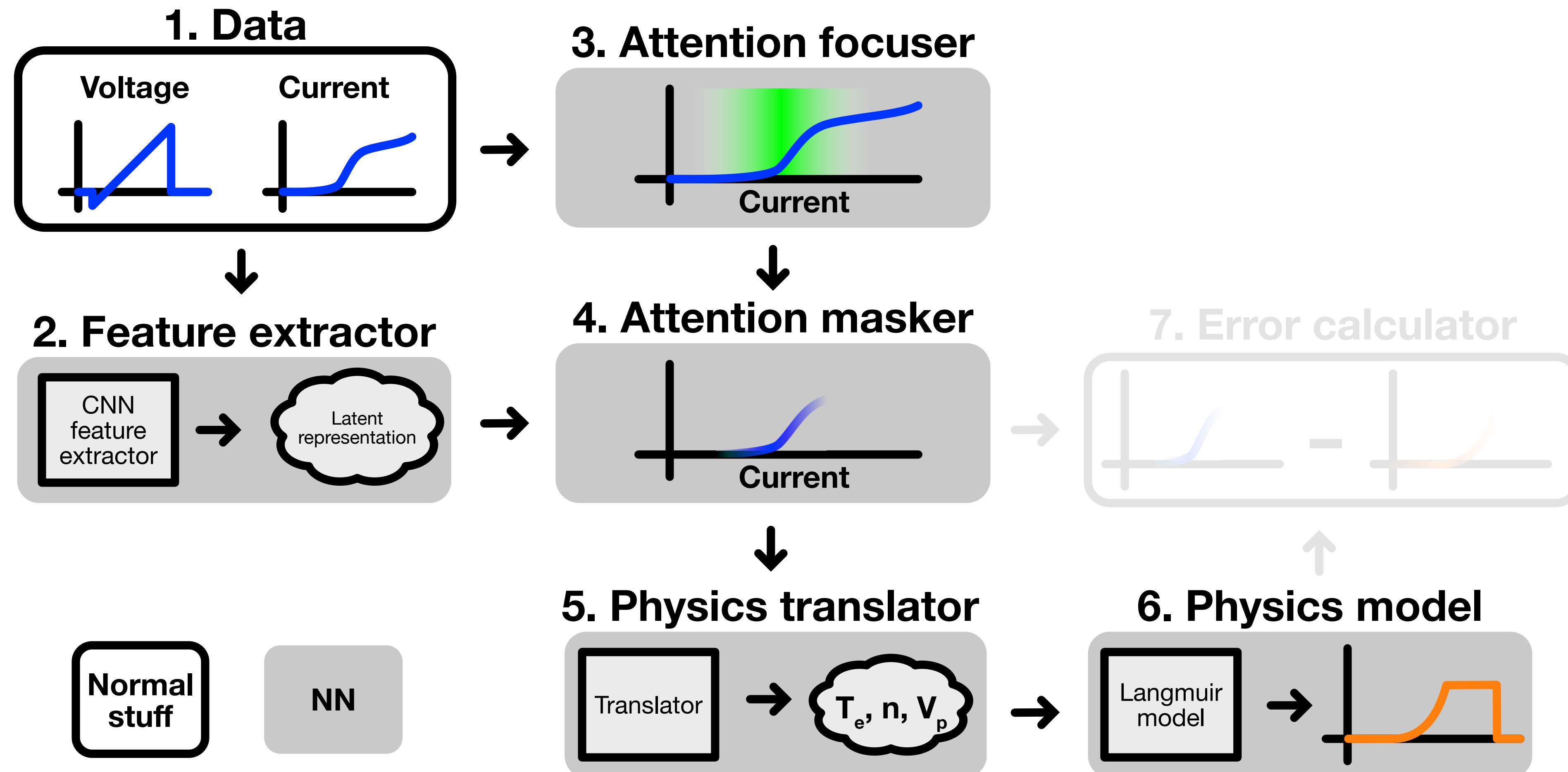
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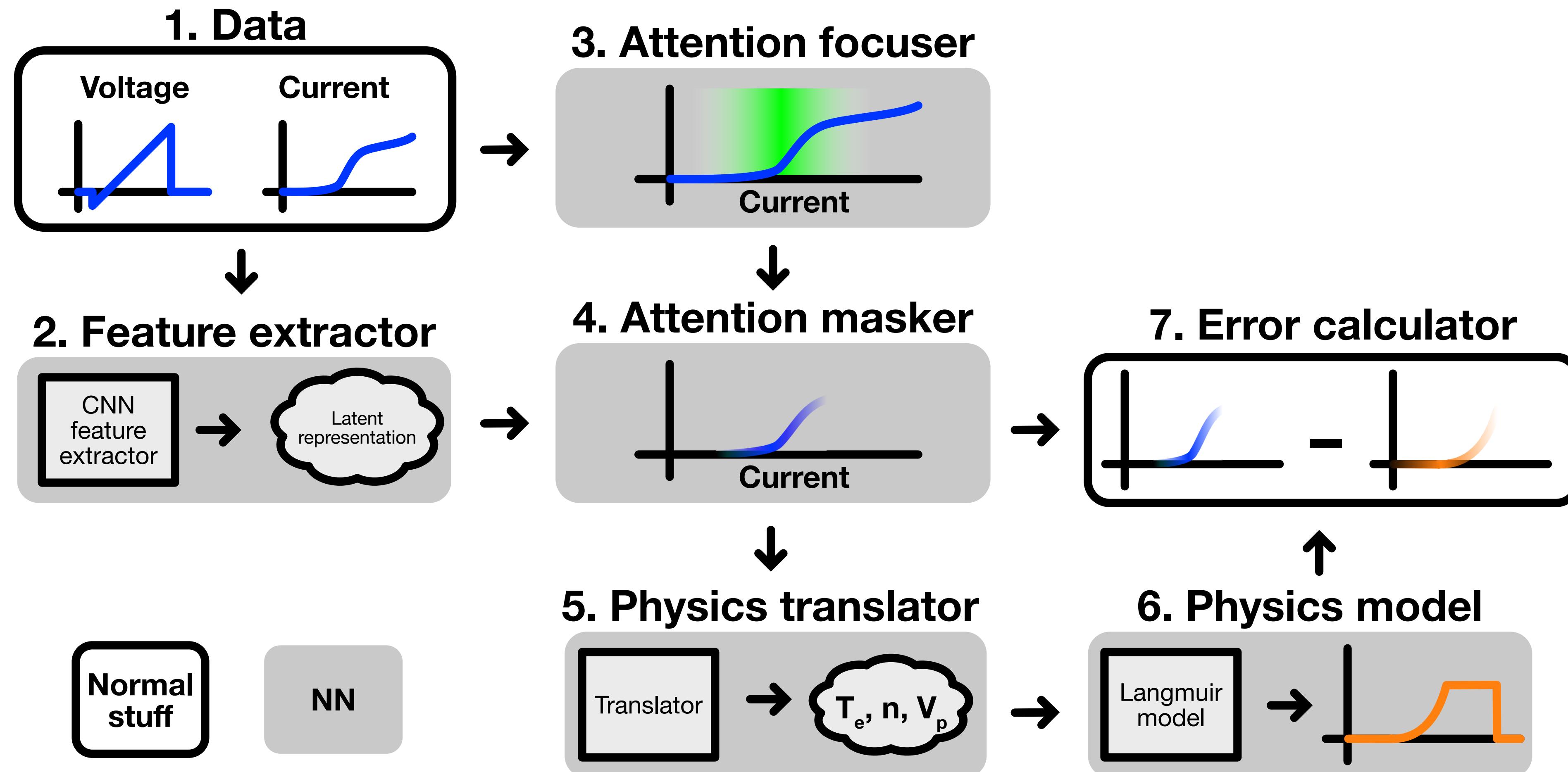
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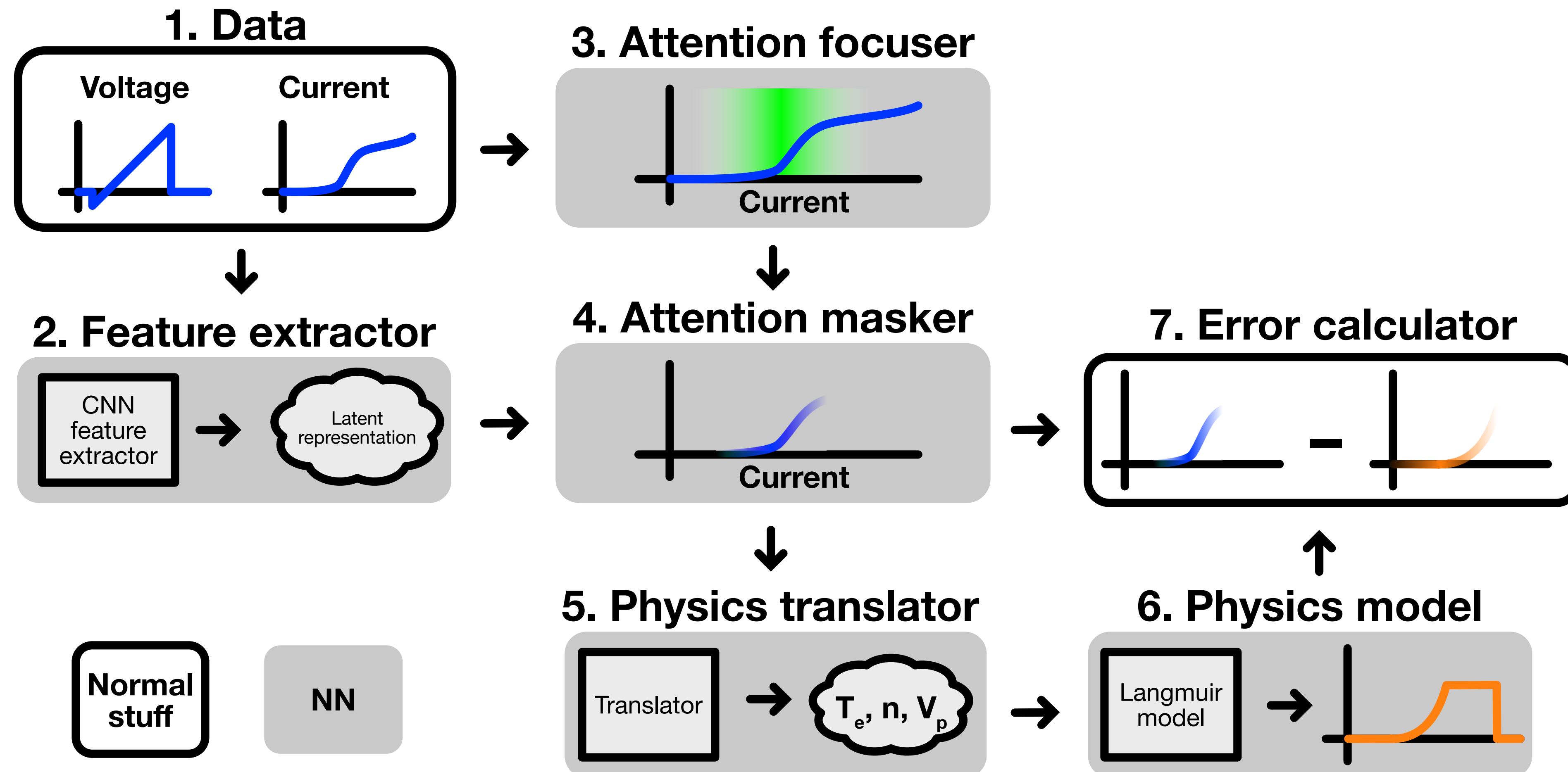
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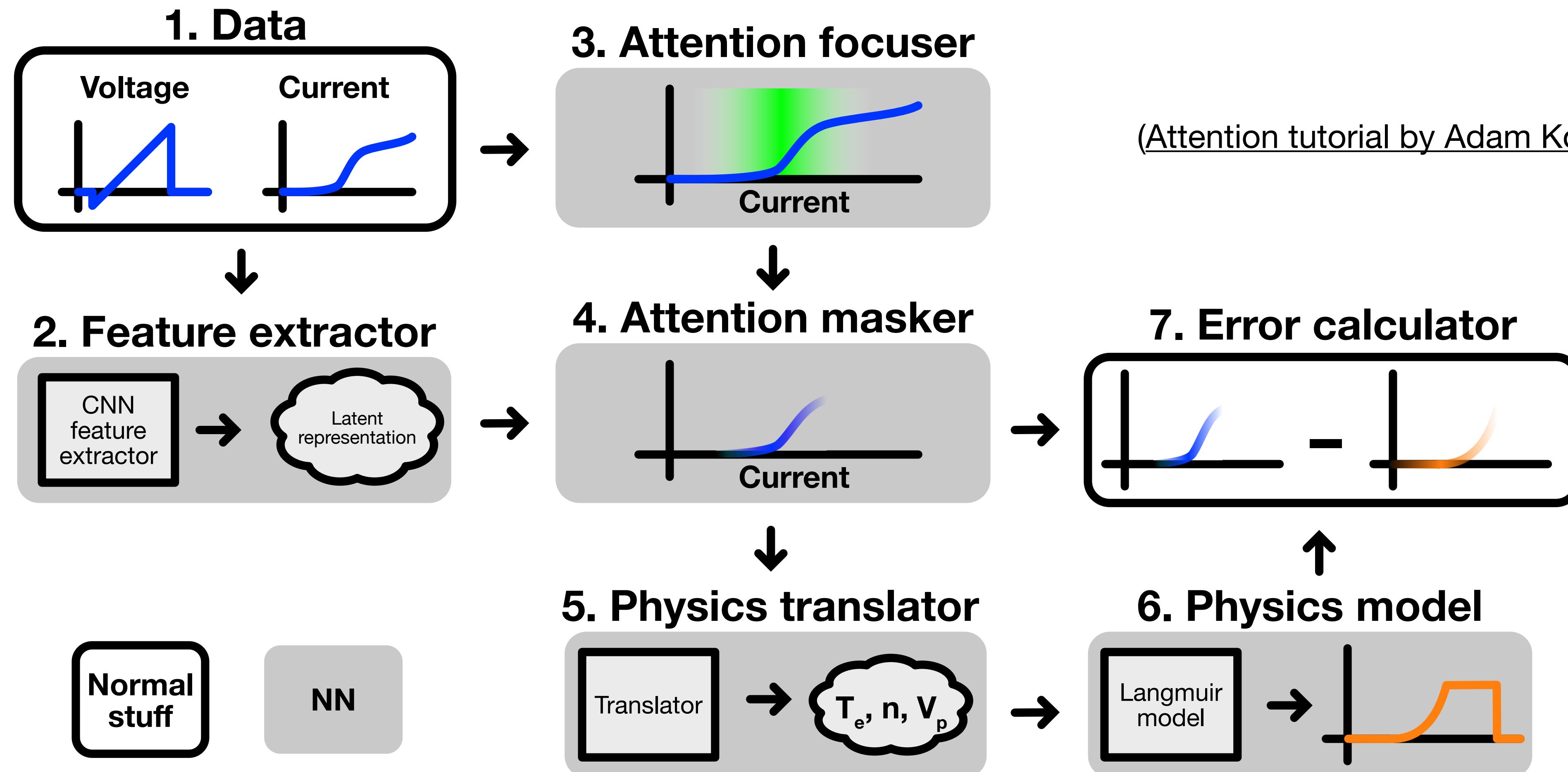


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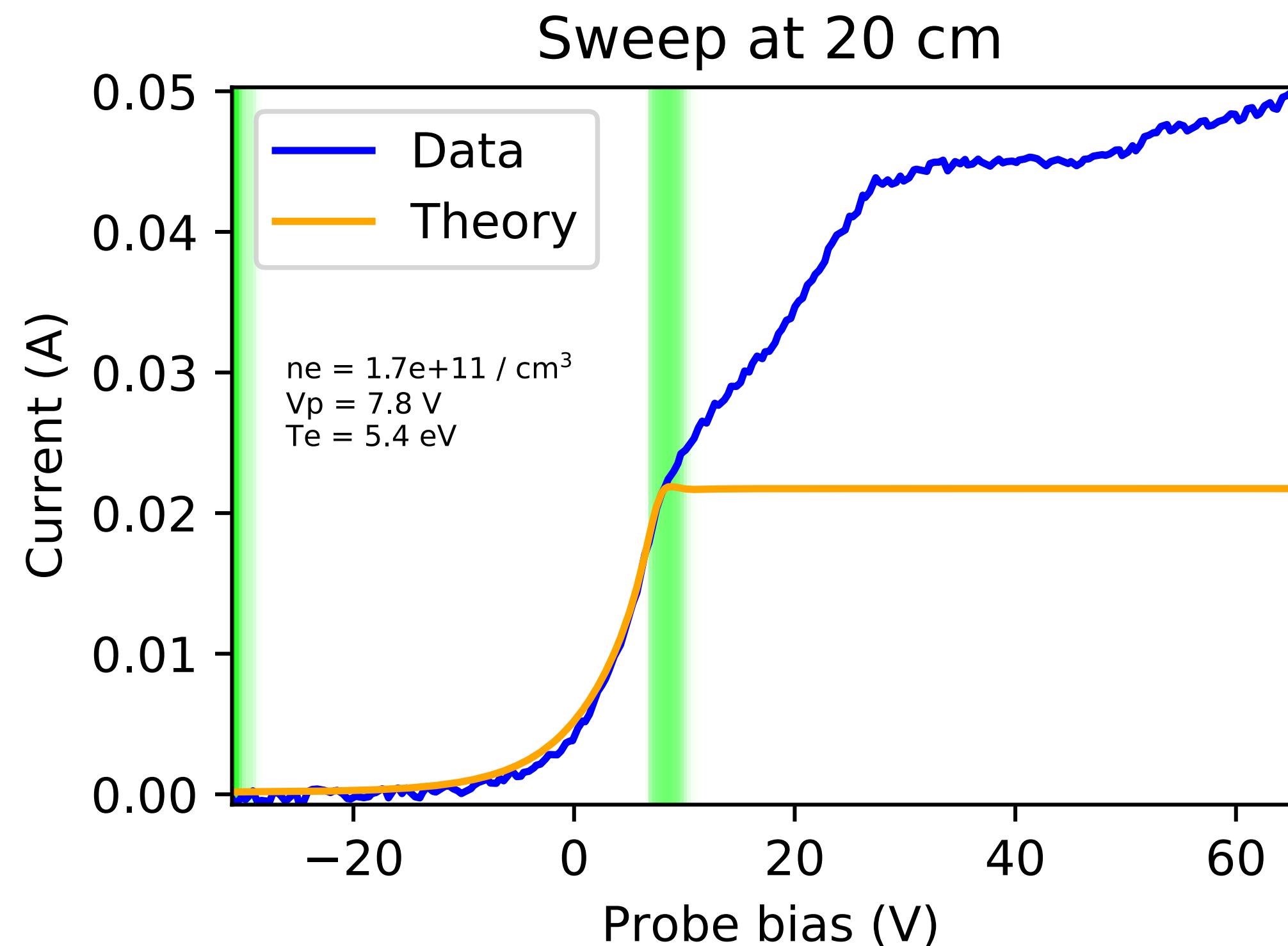
(Trained with both real and generated sweeps)

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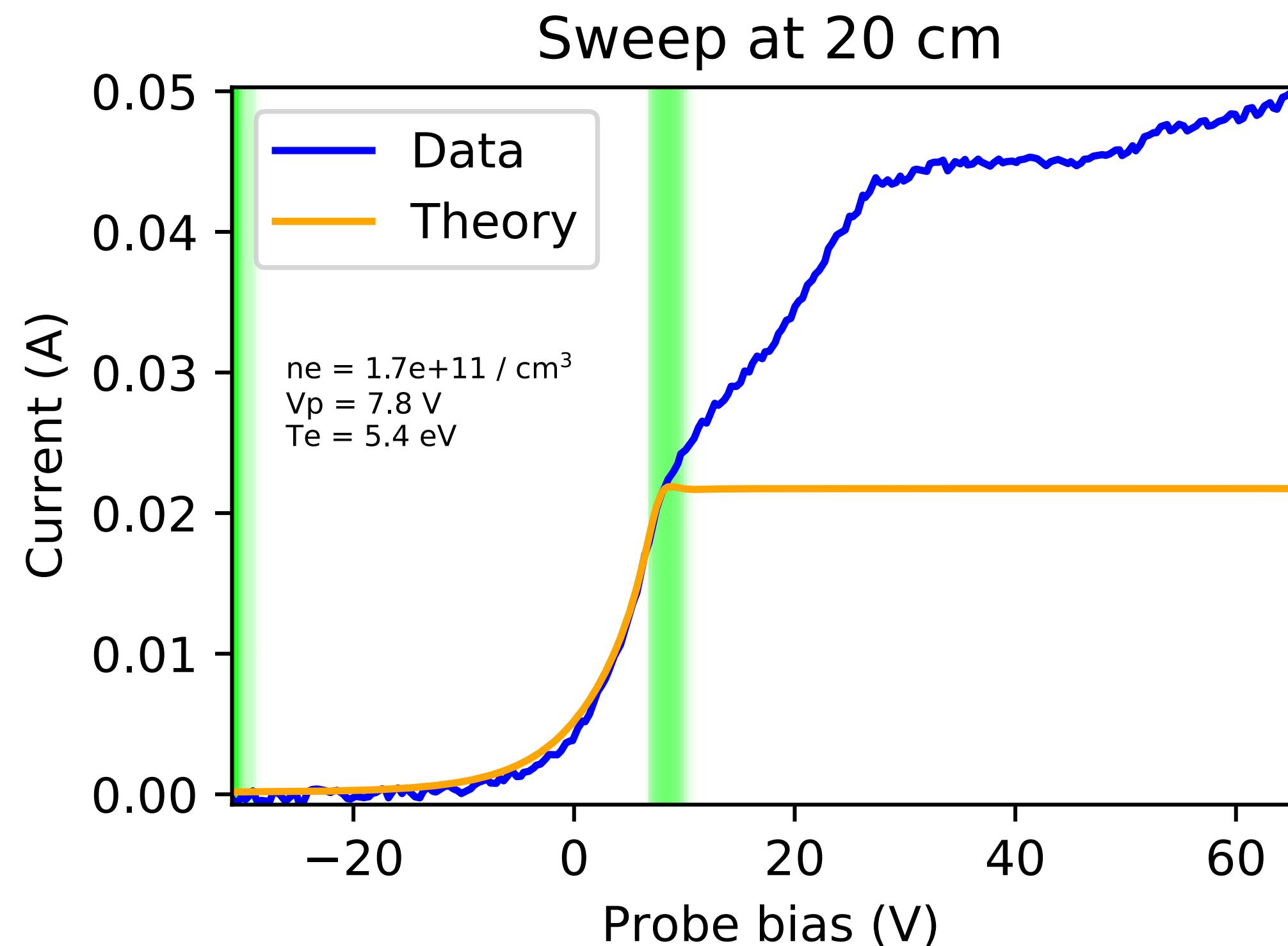


# Performance is decent (with Maxwellian distributions)

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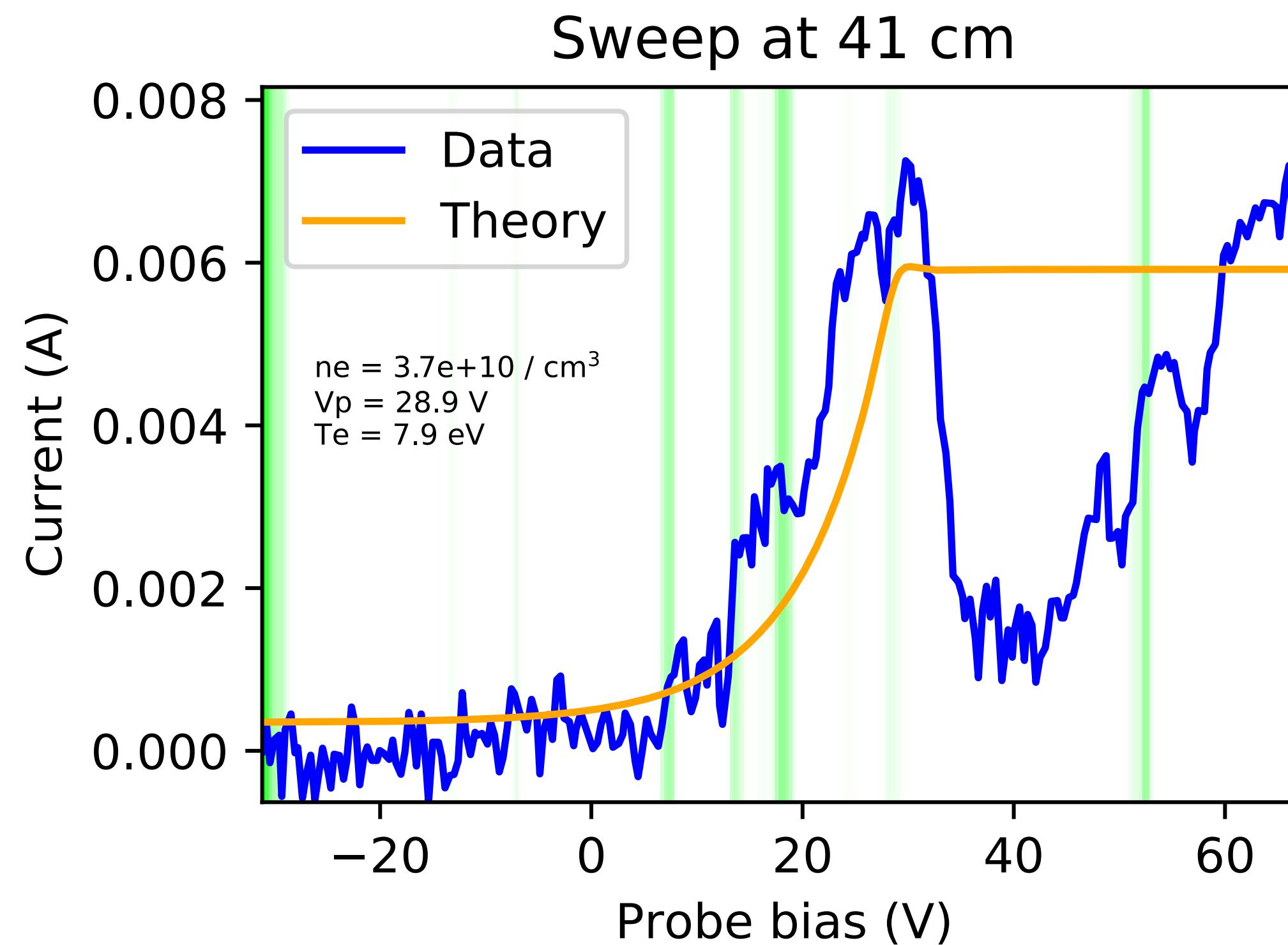


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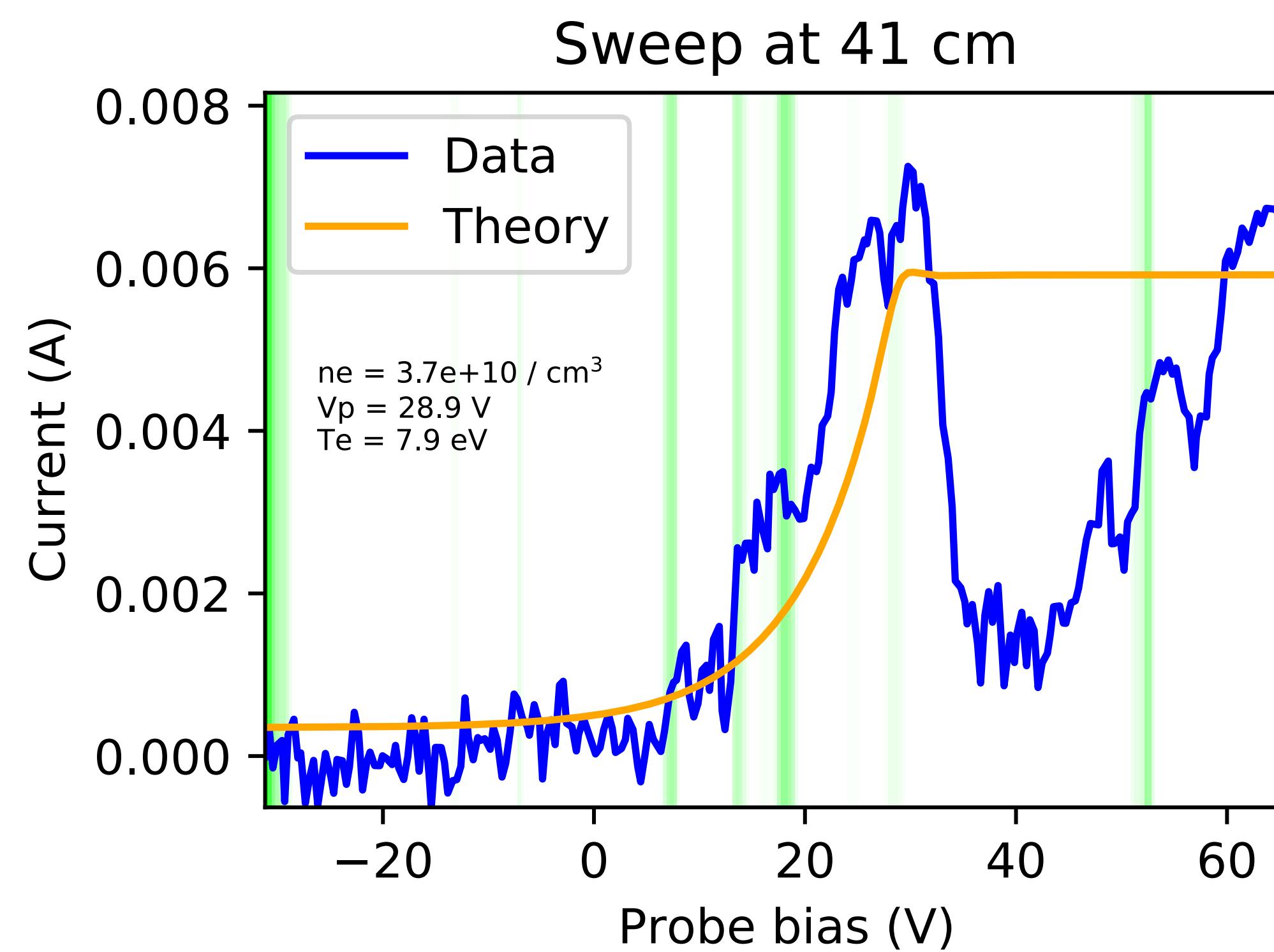
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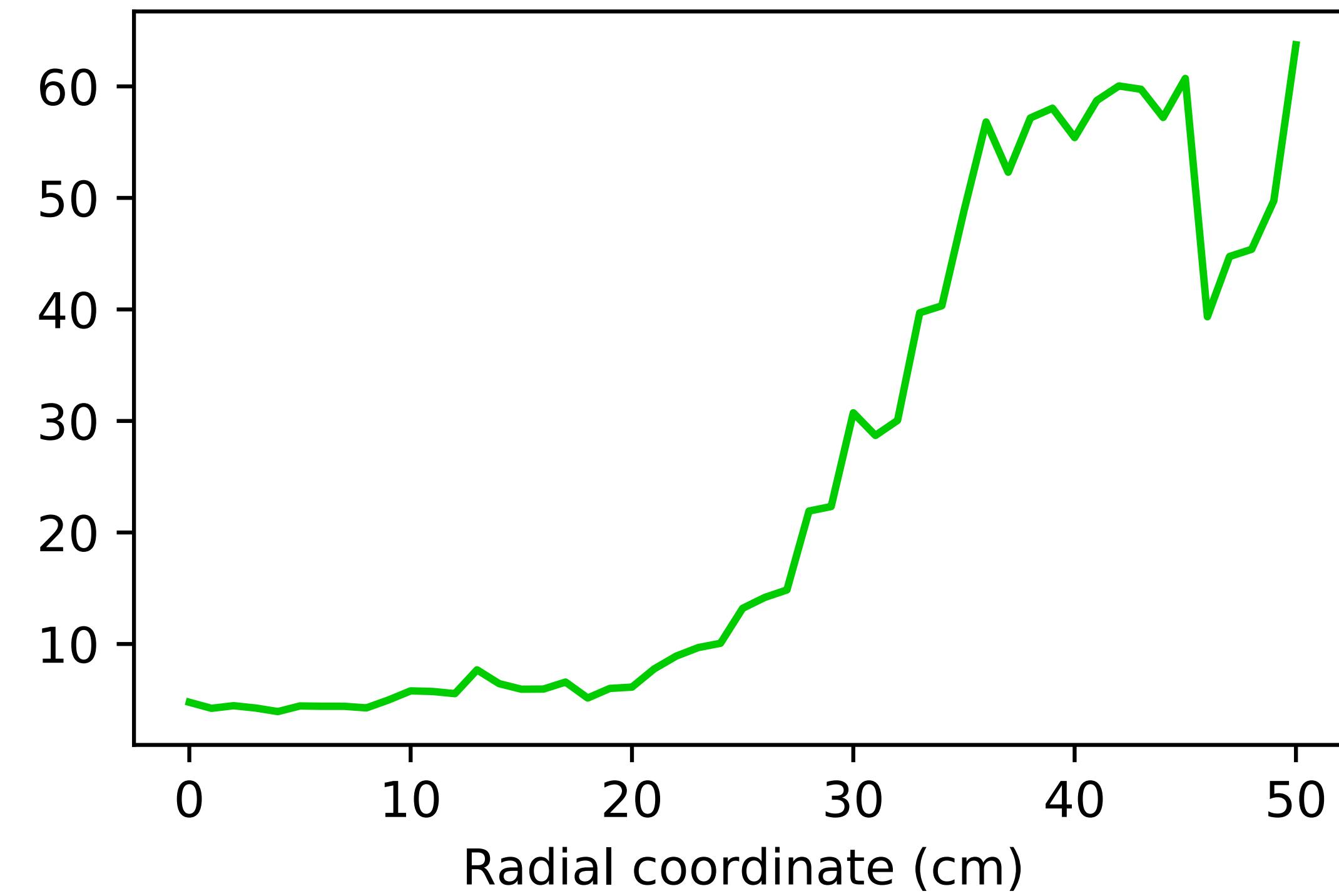


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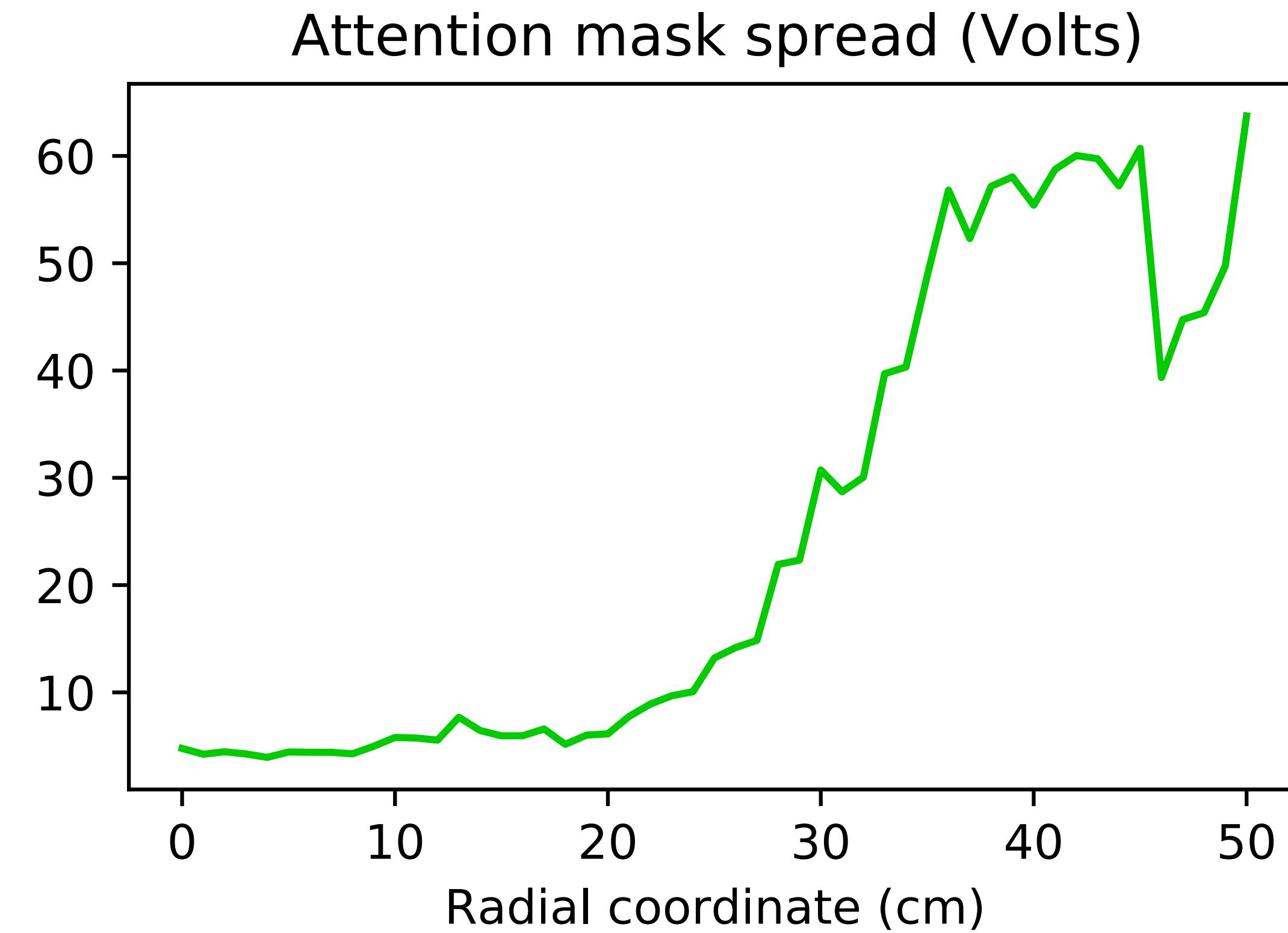
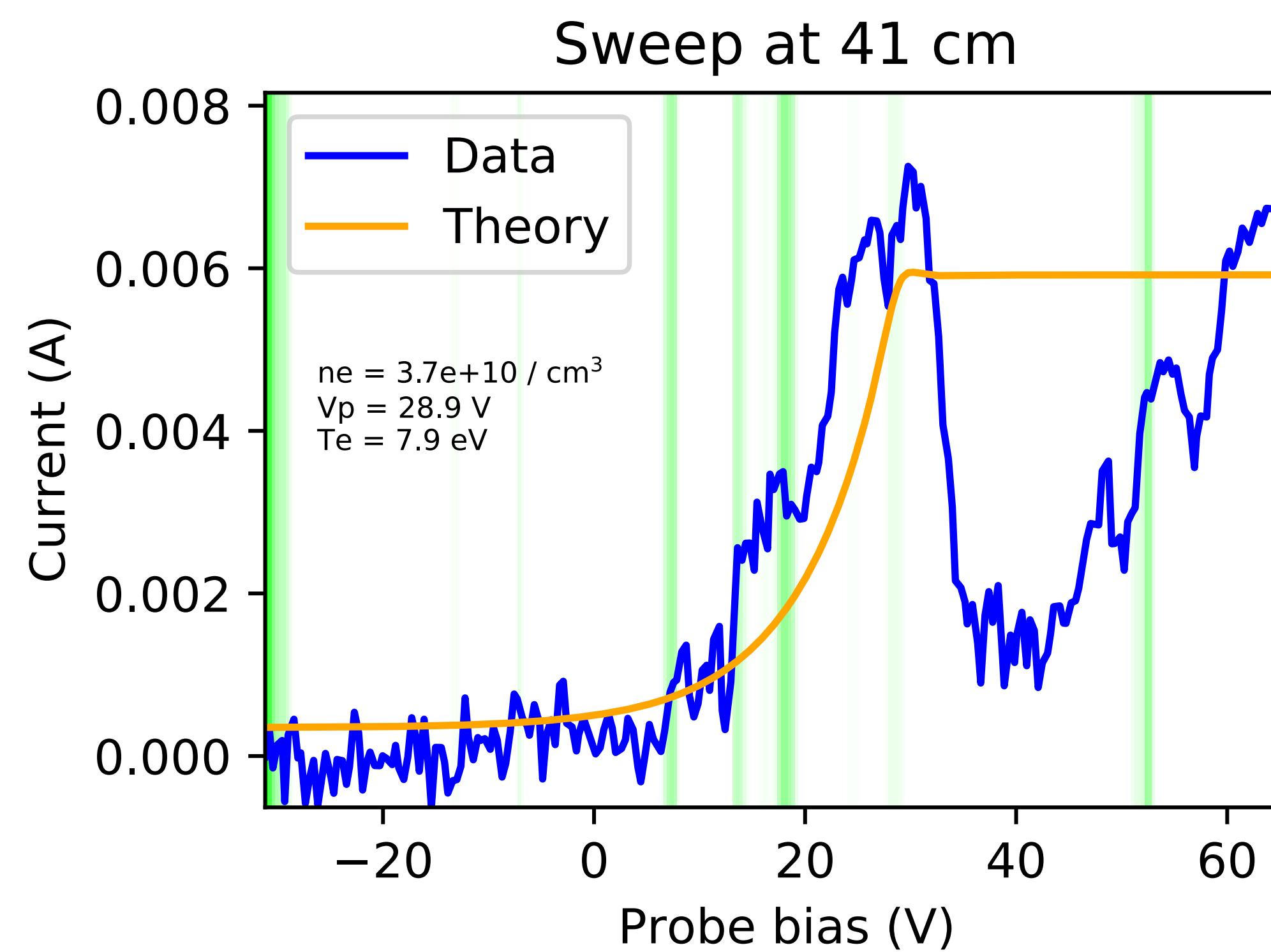


Attention mask spread (Volts)



- Attention is like a learned window

# Performance is decent (with Maxwellian distributions)



- Attention is like a learned window
- Get an uncertainty measure for free
- Can't do magic

# All the code, trained models, a bit of data can be found on Github

- <https://github.com/physicistphil/sweep-langmuir-ml>
- Requires TensorFlow ~2.2
- Train + build your own models (please contribute!)
- Will probably be rolled into [bapsflib](#)



**Github link**

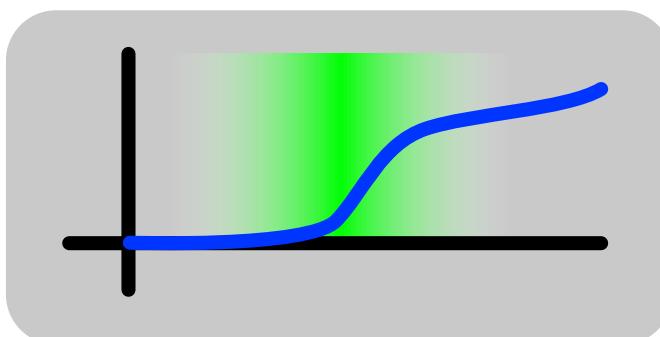
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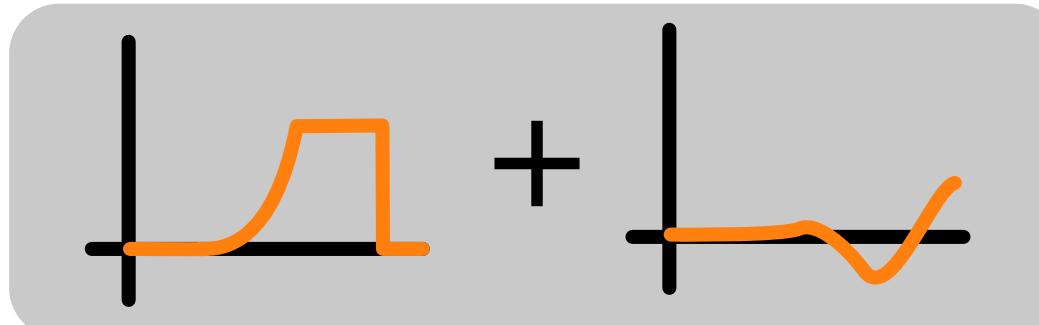


**Github link**

## 1. Attention-based



## 2. Discrepancy-based



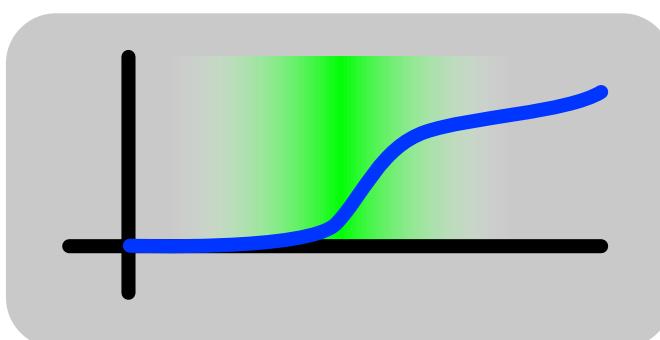
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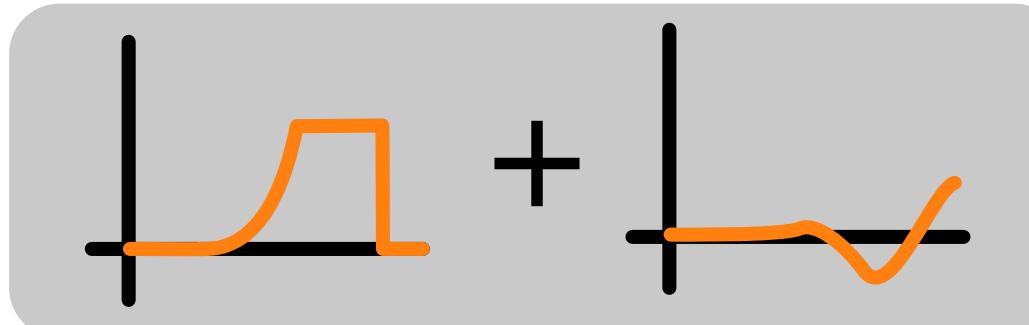


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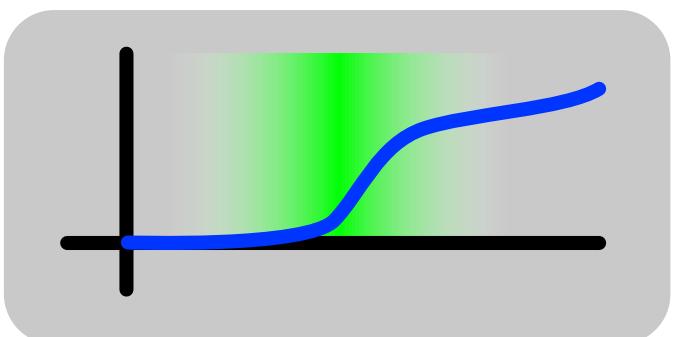
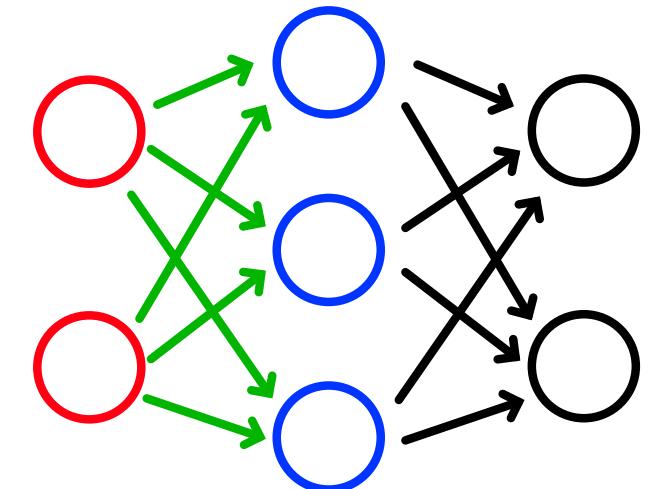


## Future plans

- Build non-Maxwellian model
- Fine tuning the models, evaluate cross-device performance
- Find contributors!

# Please enjoy the data-driven diagnostics revolution responsibly

- We use Langmuir sweeps to estimate  $T_e$  and other quantities
- Neural networks help us estimate quantities in noisier and (soon) non-Maxwellian regimes
- An attention-based approach is used to fit simple Maxwellian
- The attention mask gives us a measure of uncertainty
- Code can be found at:  
<https://github.com/physicistphil/sweep-langmuir-ml>
- I have a poster on Thursday 2-5p if you want to talk more

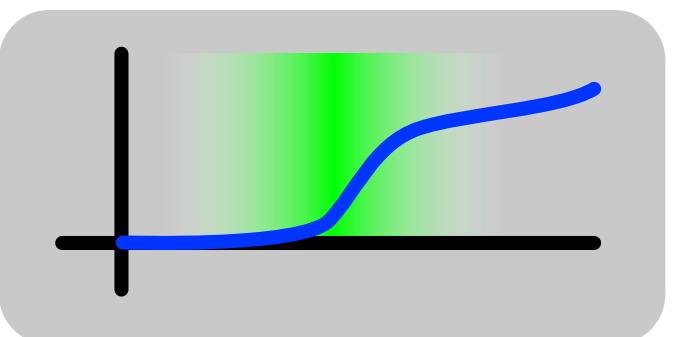
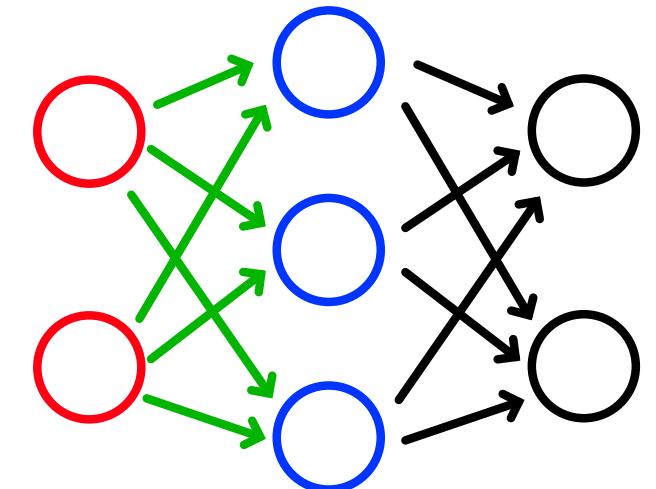


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- We use Langmuir sweeps to estimate  $T_e$  and other quantities
- Neural networks help us estimate quantities in noisier and (soon) non-Maxwellian regimes
- An attention-based approach is used to fit simple Maxwellian
- The attention mask gives us a measure of uncertainty
- Code can be found at:  
<https://github.com/physicistphil/sweep-langmuir-ml>
- I have a poster on Thursday 2-5p if you want to talk more



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[Github link](https://github.com/physicistphil/sweep-langmuir-ml)