

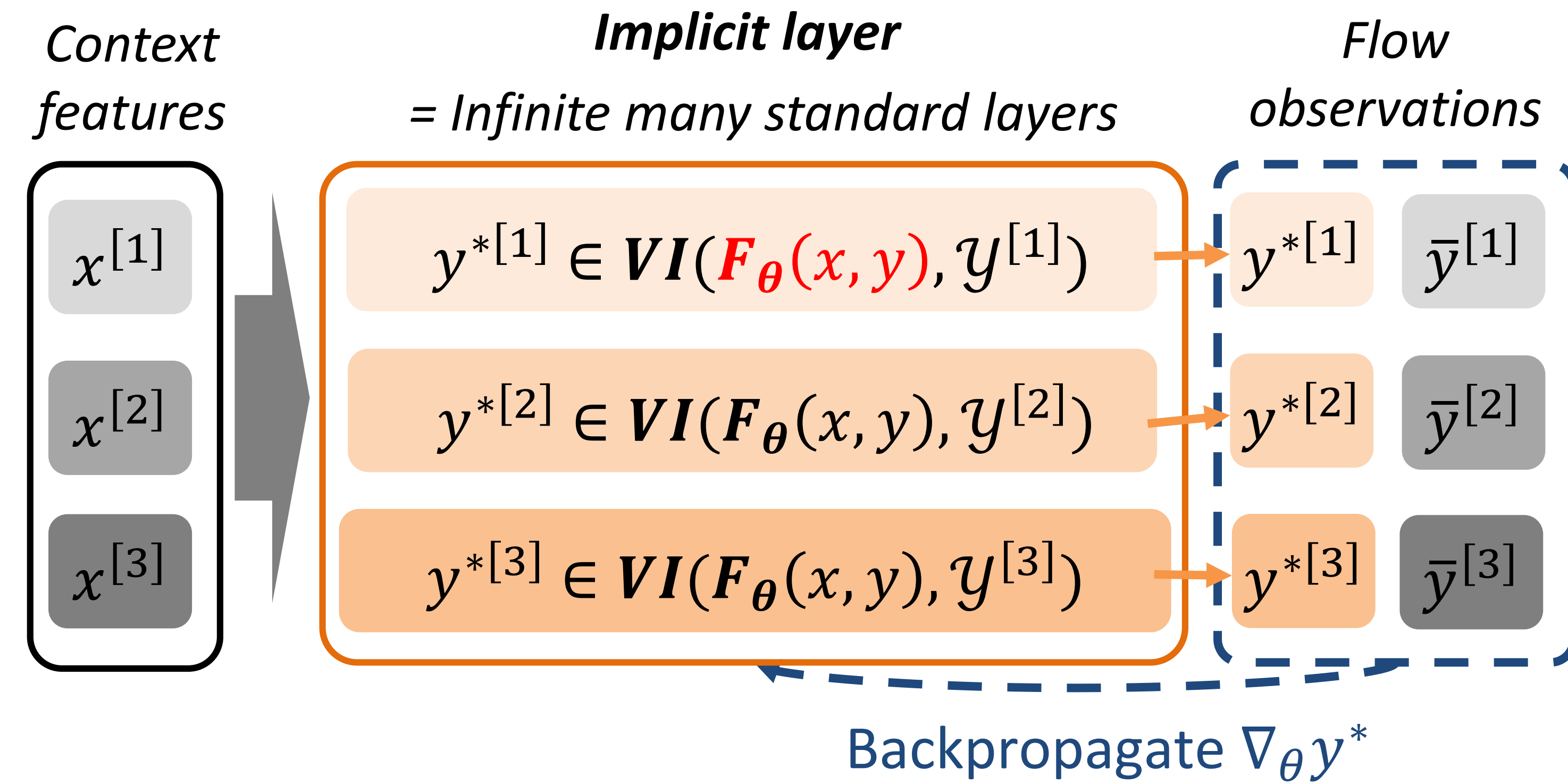
End-to-End Learning of User Equilibrium: Expressivity, Generalization, and Optimization

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2 End-to-End Framework

Consider planners observe weather and flows for three days.

- a** Approximate the travel cost function $F_\theta(x, y)$ with neural networks.

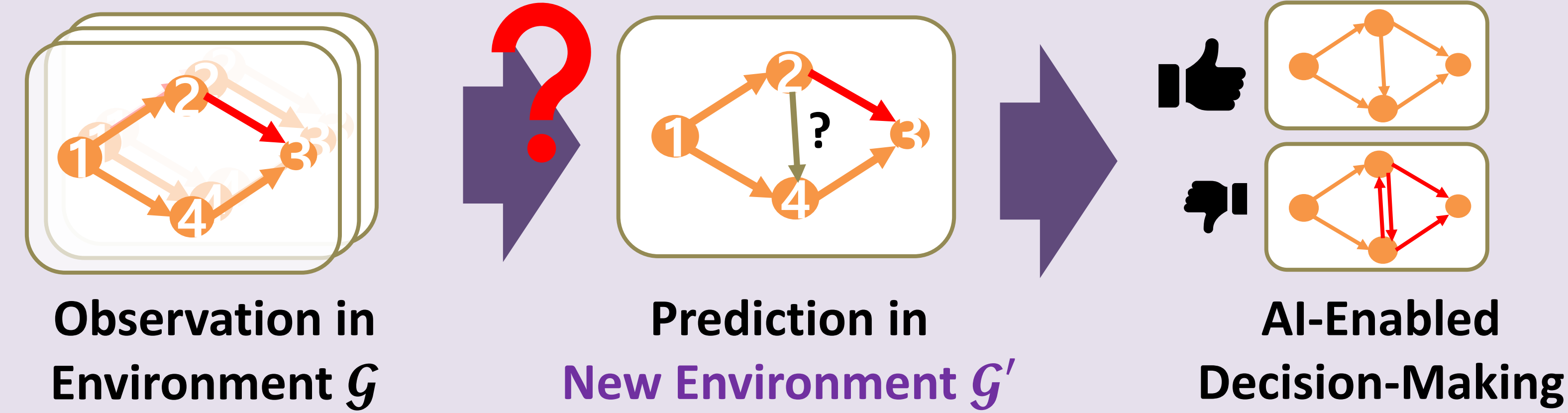


- b** Encapsulate user equilibrium with an implicit layer and solve a batch of variational inequalities.
- $$\langle F_\theta(x, y^*), y - y^* \rangle \geq 0, \quad \forall y \in \mathcal{Y}$$

- c** Auto-differentiate through the equilibrium states to learn parameter θ to minimize fitting error/

1 Research Question

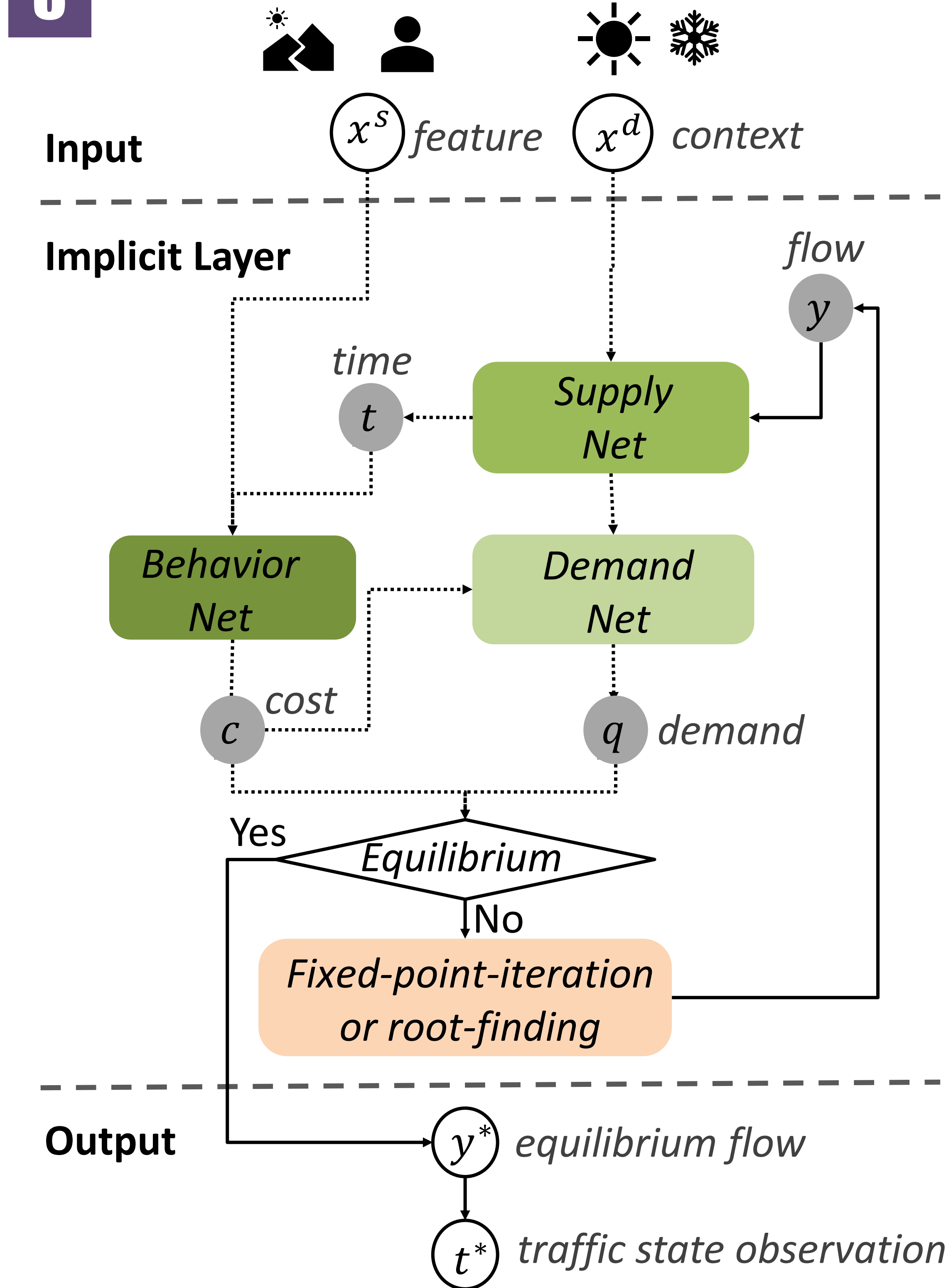
Can neural networks help planners learn a “better” traffic assignment model from real-world data ?



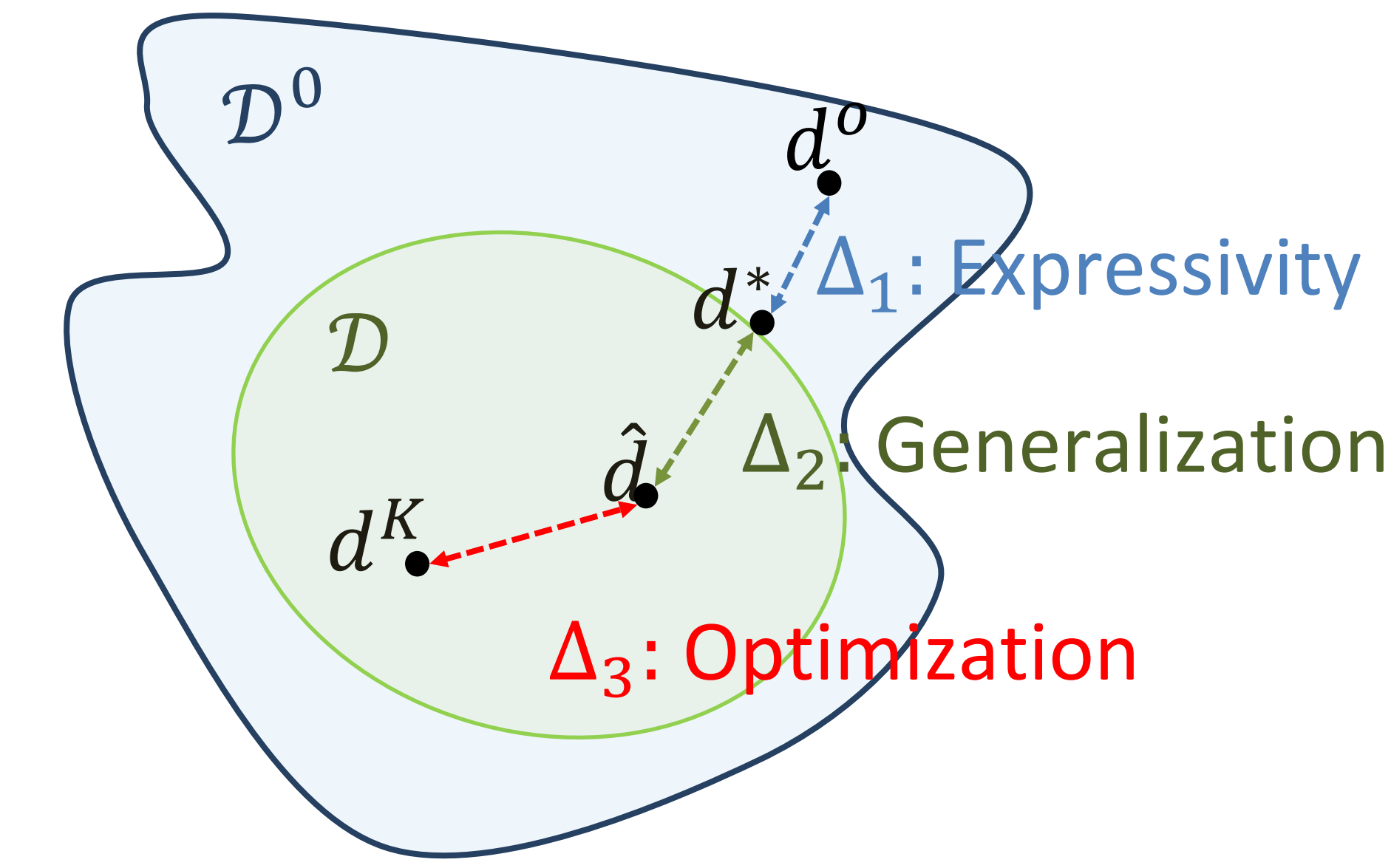
6 Main Takeaway

- Utilizing neural networks' representation power, our end-to-end framework learns a range of "well-defined" user equilibria from observed traffic states, maintaining controlled errors.
- Auto-differentiation boosts scalability and ensures local convergence in training.
- Using single-step network loading instead of user equilibrium during training may compromise performance.

3



4 Framework analysis



Total error $\Delta \leq$	Δ_1	Δ_2	Δ_3
# Parameters \uparrow	\downarrow	\uparrow	$=$
# Samples \uparrow	$=$	\downarrow	\uparrow
# Equilibrium approximation \uparrow	$=$	$=$	\downarrow

5 Case Study Chigago sketch

Model	Inverse demand function	Link performance function	Number of Parameter	Link time prediction error (%)
Functional	Context-dependent exponential function	Context-dependent BPR	4	2.93
Linear	Linear function	Standard BPR	6	12.6
End-to-end	Residual neural network	Physics-informed neural network	232	9.5

