We would like to thank all reviewers for reading our paper and providing constructive comments. Upon acceptance, we will proofread and fix all editorial issues. Below we first address a few common concerns.

Learning mode and intervention mode. In most cases, the game designer is expected to first learn about the agents (e.g. payoff functions) and then use the information (shared weights in the equilibrium layer) to design interventions. Sometimes, the primary interest is to understand agent behaviors, and hence only the learning mode is needed. Alternatively, when all game inputs are known, the focus is on the intervention mode. Thus, the two modes are both independent and integrated from the application point of view. In the final version, we will (i) explain in § 2.1 how these two modes work in different contexts; and (ii) emphasize this point in the mathematical formulation presented in § 2.2.

Relation between VI and equilibrium. We agree that it is neither rigorous nor necessary to assert that "most" equilibrium problems can be formulated as VI. Suffice it to say that VI is a powerful tool to study various equilibrium problems. In the final version we will (i) stress the connection between monotone VI problems and equilibrium problems with recommended references; and (ii) provide more examples of the equilibrium problems that can be taclked by VI.

Apply ML in real-world domains. Our work is inspired by the current interests on complex optimization-based layers. Although the field has laid a solid theoretical foundation, it has yet to fully exploit the connection between this powerful architecture and real-world problems. Our work not only adds a novel theoretical concept into the rapidly growing toolbox, but also demonstrates the potential of applying the end-to-end framework with VI layers in games.

Reviewer 1. Thanks for your generally positive view of our approach. We would like to emphasize the technical contribution of our work as follows. It is the first to treat VIs as individual layers in the end-to-end framework. We propose (i) a new algorithm (tested in Appendix B.3) for solving VI problems in forward propagation and (ii) a new sensitivity analysis method for VI, which views VI problem as a network of infinite number of QP layers, for backward propagation. Both methods are novel for VI problems.

Reviewer 2. Thanks for your comments and suggestions. Upon acceptance, we will (i) carefully separate well known results included in the analysis from our own results, (ii) treat the second example as a continuing example, and (iii) clarify the conditions used in (C.3). Below are our responses to the weaknesses identified in your report.

First, the main focus of our work is to establish the theoretical foundation of differentiable VI layers and explore how such an end-to-end framework can be used for learning and intervention in games. Thus, the experiments focus on small examples to validate the methodologies. As equilibrium layers are much more complicated than traditional layers, it cannot be solved by generic non-linear solvers in MATLAB. **Second**, we respectively disagree with the opinion that the contribution of our work is weakened by the lack of new mathematical techniques. In fact, we propose, analyze and validate two new algorithms, one for solving VI problems and the other for sensitivity analysis, as an integral part of the new framework. We also respectively disagree that Wardrop's equilibrium brings about too much required structure, because it is just a special case of the VI based layers. The proposed framework is not restricted in any way by the structure that comes with that equilibrium problem. **Third**, as explained above, the learning and intervention modes are independent in the sense of objective functions and only integrated from the application point of view. Both modes are end-to-end, because the equilibria of games are integrated into the framework as individual layers. The learning mode itself can be viewed as a generalization of the end-to-end learning framework proposed in reference [33].

Reviewer 3. Thanks for your constructive comments. Some of your concerns are addressed in the general response. Below is the answer to an important question raised in your comments.

Central designer. We agree that in some cases a game may not have a "natural" designer like the auctioneer. We define the central designer as an authority whose action can influence the outcome of the game. In congestion game, for instance, the owner of the road network (typically the "government") has the power to levy toll on roads, or implement control measures. These actions can be expected to affect how agents behave and eventually the evolution of the game. We believe that in most (if not all) games, an external designer could be created, if only virtually, to play such a role.

Reviewer 4. Thanks for your positive view of our work. We will clarify the description about convergence in § 3.2.1. The paper about AI Economist is actually reference [64], and we will add more details in the literature review.

The explicit differentiation method and the cited method. Both methods employs a specific solution in the feasible set (typically a polyhedron) to deal with the non-uniqueness issue. In the cited method, it has to be a nondegenerate extreme point. However, if such a solution is not available from the equilibrium algorithm, it has to be obtained separately, which is a burden in the end-to-end optimization. Since our method unrolls the projection method, it only works when F_λ is monotone and the projection method converges. We will clarify this point in the final version. Thanks for your advice on how to expand our results to the general monotone setting.

Example 2 and the experiment. The formulation of learning mode in the experiment is given in Example 2. In this case, f represents the number of agents on each edge (flow), which is the only observable state. Typically, it is difficult to directly measure/observe the underlying parameters, such as the time value of money and the coefficients in the hidden costs functions. Instead, they are estimated by minimizing the loss, i.e., the sum of squared errors of the equilibrium flows. We report the losses on log scale for better visualization in Figure 7.