Uni[MASK]: Unified Inference in Sequential Decision Problems

Anonymous Author(s)
Affiliation
Address
email

Abstract

Randomly masking and predicting word tokens has been a successful approach in pre-training language models for a variety of downstream tasks. In this work, we observe that the same idea also applies naturally to sequential decision making, where many well-studied tasks like behavior cloning, offline RL, inverse dynamics, and waypoint conditioning correspond to different sequence maskings over a sequence of states, actions, and returns. We introduce the Uni[MASK] framework, which provides a unified way to specify models which can be trained on many different sequential decision making tasks. We show that *a single* Uni[MASK] *model* is often capable of carrying out many tasks with performance similar to or better than single-task models. Additionally, after fine-tuning, our Uni[MASK] models consistently outperform comparable single-task models.

1 Introduction

Masked language modeling [11] is a key technique in natural language processing (NLP). Under this paradigm, models are trained to predict randomly-masked subsets of tokens in a sequence. For example, during training, a BERT model might be asked to predict the missing words in the sentence "yesterday I ___ cooking a ___". Importantly, while unidirectional models like GPT [32] are trained to predict the next token conditioned only on the left context, bidirectional models trained on this objective learn to model both the left *and* right context to represent each word token. This leads to richer representations that can then be fine-tuned to excel on a variety of downstream tasks [11].

Our work investigates how masked modeling can be a powerful idea in sequential decision problems. Consider a sequence of states s and actions a collected across T timesteps $s_1, a_1, \ldots, s_T, a_T$. If we consider each state and action as tokens of a sequence (analogous to words in NLP) and mask the last action $(s_1, a_1, s_2, a_2, s_3, _)$, then predicting the missing token a_3 amounts to a Behavior Cloning prediction with two timesteps of history [31], given that this masking corresponds to the inference $\mathbb{P}(a_3|s_{1:3}, a_{1:2})$. From this perspective, training a model to predict missing tokens from all maskings of the form $(s_1, a_1, \ldots, s_t, _, \ldots, _)$ for all $t \in [1, \ldots, T]$ corresponds to training a Behavior Cloning (BC) model.

In this work, we introduce the Uni[MASK] framework: **Uni**fied Inferences in Sequential Decision Problems via [MASK]ings, where inference tasks are expressed as *masking schemes*. Through this framework, commonly-studied tasks such as goal or waypoint conditioned BC [13, 35], offline reinforcement learning (RL) [25], forward or inverse dynamics prediction [20, 9, 5], initial-state inference [37], and others can be unified under a simple sequence modeling paradigm. In contrast to standard approaches that train a single-task model for each inference task, we show how this framework naturally lends itself to multi-task training: a single Uni[MASK] model can be trained to perform a variety of tasks out-of-the-box by appropriately selecting sequence maskings at training time.

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We test this framework in a gridworld navigation task and a continuous control environment. First, we train a Uni[MASK] model by sampling from the space of all possible maskings at training time (random masking) and show how this scheme enables a single Uni[MASK] model to perform BC, reward-conditioning, waypoint-conditioning and more by conditioning on the appropriate subsets of states, actions, and rewards. We then systematically analyze how the masking schemes seen at training time affect downstream task performance. Training on random masking generally does not compromise single-task performance, and in fact can outperform models that only train on the task of interest. In the continuous control environment, we confirm that a model trained with random masking and fine-tuned on BC or RL outperforms models specialized to those tasks.

Our results suggest that expressing tasks as sequence maskings with the Uni[MASK] framework may be a promising unifying approach to building general-purpose models capable of performing many inference tasks in an environment [2], or simply offer an avenue for building better-performing single-task models via unified multi-task training.

In summary, our contributions are:

1. We propose a new framework, Uni[MASK], that unifies inference tasks in sequential decision problems as different masking schemes in a sequence modeling paradigm.
2. We demonstrate how randomly sampling masking schemes at training time produces a single multi-inference-task model that can do BC, reward-conditioning, dynamics modeling, and more out-of-the-box.
3. We test how training on many tasks affects single-task performance, and show how fine-tuning models trained with random masking consistently outperforms single-task models.
4. We show how the insights we have gained while developing our choice of Uni[MASK] architecture can be used to improve other state-of-the-art methods.

2 Related Work

Transformer models. Our work is motivated by the huge success of transformer models [38] in other domains such as NLP [11, 32, 3] and computer vision [14, 21]. Using transformers in RL and sequential decision problems has proven difficult due to the instability of training [29], but recent work has investigated how to use transformers in model-based RL [6], motion forecasting [28], learning from demonstrations [33], and tele-operation [10].

The utility of randomized masking. In addition to being used as one of the main training objectives for BERT (the "cloze task", [11]), the flexibility afforded by randomized masking in bidirectional models has been utilized in other previous works applied to language [19, 27] and vision [4] – mostly for the purpose of speeding up auto-regressive decoding, which is not our focus.

Sequential decision-making as sequence modeling. [7] and [22] focus on RL and show how one can use GPT-style (causally-masked) Transformer models to directly generate high-reward trajectories in an offline RL setting. Unlike this line of work, we focus on many tasks that a sequence modeling perspective enables one to do, rather than just offline-RL. While some previous work has cast doubt on the necessity of using transformers to achieve good results in offline RL [15], we note that offline RL [25] is just one of the various tasks we consider. Concurrent work to ours generalizes the left-to-right masking in the Transformer to condition on future trajectory information for tasks such as state marginal matching [18] and multi-agent motion forecasting [28]. In contrast, we systematically investigate how a single bidirectional Transformer can be trained to perform arbitrary downstream tasks (in more complex settings than motion forecasting—i.e., we also consider agent actions and rewards in addition to states). The main thing that sets us apart from these works is a systematic view of all tasks that can be represented by this sequence-modeling perspective, and a detailed investigation of how different multi-task training regimes compare.

Self-supervised learning for sequential decision problems. Training on random maskings of one's data can be considered as a form of self-supervised learning. Previous work on self-supervised learning is mostly focused on improving RL by training models on auxiliary objectives such as state dynamics prediction [36] or intrinsic motivation [30]. Typically, to accomplish the tasks we consider, prior work relies on single-task models: for example, goal-conditioned imitation learning [12], RL [23], waypoint-conditioning [35], property-conditioning [40, 18], or dynamics model

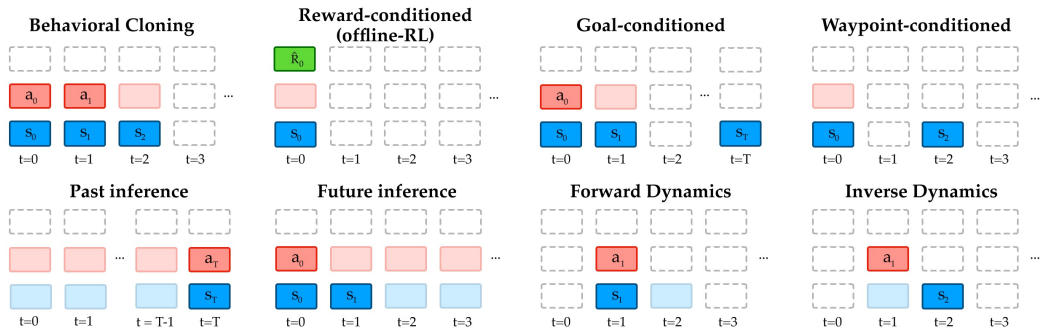

Figure 1: Uni[MASK] **framework: Representing arbitrary tasks as masking schemes.** For each task, we show the inputs to the model (solid colors) and the outputs the model must predict (translucent colors). For example, in future inference, the model must predict all future states and actions conditioned on the initial states and actions. Here we only display one input masking scheme for each task, even though there might be multiple that are valid or necessary (e.g. BC will have up to T different masking schemes, one for each possible history length—although in practice one would generally use the model with a sliding window).

learning [20, 9]. Another recent work [34] focuses on scaling up transformer models to be able to handle multi-modal input from a large variety of different environments (which they call "tasks" – *which is different from our usage of the word!*). We instead demonstrate how sequence modeling can be a unifying framework for formulating and performing any inference task within an environment with a single model.

3 The Uni[MASK] Framework

We introduce the Uni[MASK] framework. In Section 3.1 we propose a unifying interpretation of inference tasks in sequential decision problems as masking schemes. In Section 3.2 we describing different ways of training Uni[MASK] models, an provide hypotheses about their efficacy.

We model trajectories as sequences of states, actions, and (optionally) property tokens:[1]

$$\tau = \{(s_0, a_0, p_0), \ldots, (s_T, a_T, p_T)\}.$$

Any property of the decision problem can be considered a "property token", including specific environment conditions being satisfied, the style of the agent, or the performance of the agent (e.g. the reward obtained in the timestep). Motivated by canonical problems in decision making that involve reward, in almost all of our analysis and experiments we consider the return-to-go property (the sum of rewards from timestep t to the end of the episode): that is, we set $p_t = \hat{R}_t$ where $\hat{R}_t = \sum_{t'=t}^{T} r_{t'}$.

3.1 Tasks as Masking Schemes

In the Uni[MASK] framework, we formulate tasks in sequential decision problems as input masking schemes. Formally, a masking scheme specifies which input tokens are masked (determining what tokens are shown to the model for prediction) and which outputs of the model are masked before computing losses (determining which outputs the model should learn to predict). For example, the masking scheme for BC unmasks (conditions on) $s_{0:t}$ and $a_{0:t-1}$, and the model must predict a_t.

In Figure 1, we illustrate how commonly-studied tasks such as BC, goal and waypoint conditioned imitation, offline RL (reward-conditioned imitation), and dynamics modeling can be unified under this representation of tasks as masking schemes. We describe the masking scheme for each of these tasks in detail in Appendix A.1.

3.2 Model Architecture & Training Regimes

Throughout the body of this, we instantiate our Uni[MASK] framework with the BERT architecture [11] consisting stacked bidirectional transformer encoder (self-attention) layers and positional encod-

[1] While reward-to-go (or other trajectory statistics) are not necessary, we formulate the most general form to showcase how one can easily condition on additional properties of a trajectory if available. Using reward-to-go also enables us to baseline our method against previous offline-RL work [7].

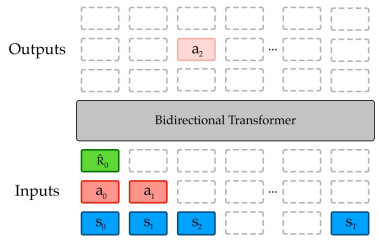

Figure 2: The Uni[MASK] model takes in a snippet of a trajectory which is masked according to a masking scheme before inference time. For each input possible masking, there are (many) corresponding tasks of predicting the missing inputs. Above we show an input masking corresponding to conditioning on both reward *and* final (goal) state; we highlight the output corresponding to predicting the agent's next action, i.e. performing the inference $\mathbb{P}(a_2|s_{0:2,T}, a_{0:1}, \hat{R}_0)$.

ings, as shown in Figure 2, adapted to the sequential decision problem domain. See Appendix A.5 for experiments with an alternative instantiation as a feedforward neural network architecture.

We stack the state, action, and property (e.g. return-to-go) tokens for each timestep into a single vector. For reward-conditioned tasks, in each context window we only feed the first return-to-go token into the model along with the number of timesteps remaining in the horizon. This information is sufficient for reward-conditioning at inference time, and we found that it outperformed the alternative of feeding in the RTG token at every timestep, as done in previous work [7, 22]. See Appendix A.3.

3.2.1 Training regimes

We experiment with four **training regimes**, illustrated in Figure 3 and described below.

`single-task`**.** Training on just one of the masking scheme described in Section 3.1.

Intuition: A single, unified interface for all tasks (data pipeline, neural architecture, etc.), where only the masking schemes needs to be varied for different tasks. This is a feature of Uni[MASK] *as a whole, so we think of* `single-task` *as a baseline training regime.*

`multi-task`**.** Training a single model on multiple masking schemes.[2]

Intuition: A single model should perform well on any of the multiple tasks on which it was trained. Additionally, it might outperform `single-task` *on individual tasks, as the model may learn richer representations of the environment from the additional masking schemes.*

`random-mask`**.** Training a single model on a randomized masking scheme.[3]

Intuition: A single model should perform well on any *sequence inference task, without requiring to specify the tasks of interest at training time. The model may learn representations even richer than that of* `multi-task` *as the model must reason about* all *components of the environment.*

`finetune`**.** Fine-tune a model pre-trained in `random-mask` on a specific masking scheme.

Intuition: A fine-tuned model benefits from the improved representations obtained from `random-mask`*, while specializing to the single task at hand.*

3.2.2 Hypotheses

Based on the intuition of the strengths of each training regime, we formulate the following hypotheses:

H1. First training on multiple inference tasks will lead to better performance on individual tasks than only training on that inference task: {`multi-task`, `random-mask`, `finetune`} > `single-task`.

H2. Random masks training outperforms training on a specific set of tasks: `random-mask` > `multi-task`.

So, **H1** tests whether models indeed learn richer representations by training on multiple inference tasks. **H2** tests a stronger claim: whether training on *all* possible tasks by randomly sampling maskings at training time is better than selecting a set of specific maskings.

[2] Sample a random trajectory snippet and apply a masking schemes from Section 3.1 (chosen at random).

[3] Sample a random trajectory snippet and mask each token at random.

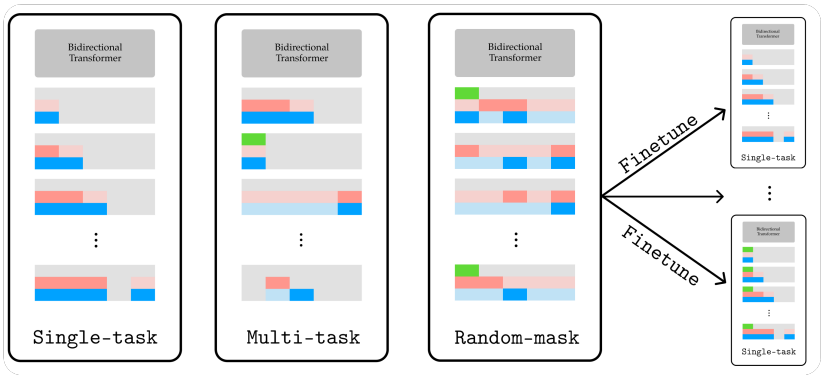

Figure 3: **The four training regimes considered in this work:** `single-task`, `multi-task`, `random-mask` and `finetune`.

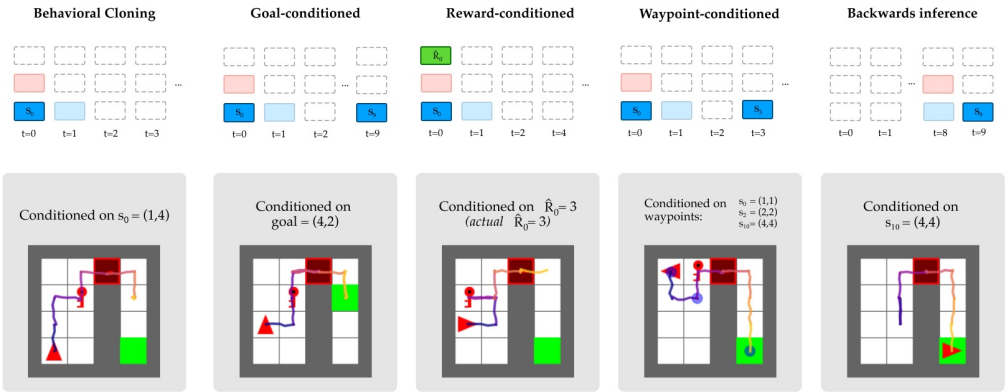

Figure 4: **A** Uni[MASK] **model trained with random masking queried on various inference tasks. (1) Behavioral cloning:** generating an expert-like trajectory given an initial state. **(2) Goal-conditioned:** reaching an alternative goal. **(3) Reward-conditioned:** generating a trajectory that achieve a particular reward, e.g., by taking a suboptimal path that does not directly reach the goal. **(4) Waypoint-conditioned:** reaching specified waypoints (or subgoals) at particular timesteps, e.g. going down on the first timestep instead of immediately picking up the key. **(5) Backwards inference:** generating a likely *history* conditioned in a final state (by sampling actions and states backwards). Trajectories are shown with jitter for visual clarity.

4 A Unified Model for Any Inference Task

We first demonstrate how `random-mask` enables a single Uni[MASK] model to perform arbitrary inference tasks at test-time on a gridworld environment, without the need for task-specific output heads or training schemes that are customized for the downstream task. We then show that `random-mask` does not compromise performance on most specific tasks of interest. Models trained with `random-mask` achieve comparable or better performance to `single-task` and `multi-task`-models, and in fact consistently outperform after additional fine-tuning on the task of interest (`finetune`).

Environment Setup. We design a fully observable 4×4 gridworld in which the agent should move to a fixed goal location behind a locked door with the MiniGrid environment framework [8]. The agent and key positions are randomized in each episode. The agent receives a reward of 1 for each timestep it moves closer to the goal, -1 if it moves away from the goal, and 0 otherwise. We train Uni[MASK] models on training trajectories of sequence length $T = 10$ from a noisy-rational agent [41]. More detailed information about the environment is in Appendix A.4.

4.1 One Model to Rule Them All

As shown in Figure 4, a single Uni[MASK] model trained with `random-mask` can be used for arbitrary inference tasks by conditioning on specific sets of tokens. Unless otherwise indicated, we take the

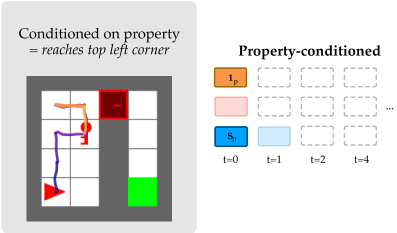

Figure 5: **Other types of property-conditioning.** If the training dataset is additionally labeled with property indicators (e.g. whether the trajectory passes by the top left corner of the grid *at any timestep*), the model can roll out trajectories conditioned on whether the property is exhibited.

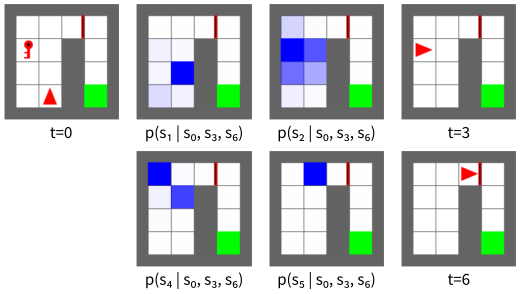

Figure 6: **Predicted state distributions.** The model is conditioned on states at $t = 0, 3, 6$.

highest probability action from the model $a_t = \arg\max_{a'_t} \mathbb{P}(a'_t \mid s_0, a_0, \ldots, s_t)$, and then query the environment dynamics for the next state s_{t+1}. The model can be used for imitation, reward- and goal-conditioning, or as a forward or inverse dynamics model (when querying for state predictions, as in the backwards inference task). If trajectories are labeled with properties at training time, the model can also be used for property-conditioning. In Figure 5, we show how the model can be conditioned on global properties of the trajectory (as opposed to conditioning on states or actions at specific timesteps), such as whether the trajectory passes through a certain position at any timestep.

Qualitatively, these results suggest that the model is capable of generalizing across masking schemes, since seeing the exact masking corresponding to a particular task at training time is exceedingly rare (out of $2^T \times 2^T \times 2$ possible state, action, and reward maskings for a sequence of length T).

4.2 Future State Predictions

Uses of the `random-mask`-trained Uni[`MASK`] model are not limited to rolling out new trajectories (requesting inferences about the agent's next action). One can also request inferences for states and actions further into the future: e.g., "where will the agent be *in 3 timesteps*?". Given a fixed initial set of observed states, we visualize the distribution of predicted states at each timestep in Figure 6. Since we do not roll out actions, querying the model for the predicted state distribution at a particular timestep marginalizes over missing actions; for example, $\mathbb{P}(s_1 \mid s_0, s_3, s_6)$ models the possibility that the agent chooses either up or left as the first action. Qualitatively, the state predictions suggest that the model accurately captures the environment dynamics and usual agent behavior; e.g. it correctly models that the agent has equal probability of going up and right at $t = 3$ (leading it to the distribution over states at $t = 4$), and that the agent must be at position (2, 1) at $t = 5$ in order to reach the door at $t = 6$.

4.3 Measuring Single-Task Performance

Next, we investigate how `random-mask` performs on individual tasks, in comparison to a `single-task` trained exclusively on the evaluated task. . For this set of experiments, we primarily consider validation loss as our measure of performance. Validation loss provides a general way to evaluate how well models fit the distribution of trajectories and transitions, which is primarily what we are concerned with for most inference tasks: i.e., how well can the network predict the true state or action in the data (e.g. next-action prediction for behavior cloning)?

In Figure 7, we report validation loss if the model is trained on one task (or multiple tasks) and evaluated on another task. As expected, models that have been trained on one masking (e.g. BC; predicting the next action conditioned on the past) perform poorly when queried with another task (e.g. predicting the previous states conditioned on the final state; past inference).

We find that many-task models (`multi-task` and `random-mask`) perform comparably (or better) to `single-task`. Specializing a model trained on multiple tasks via finetuning (`finetune`) leads to the best performance, outperforming `single-task` on all tasks except BC and forward dynamics. These

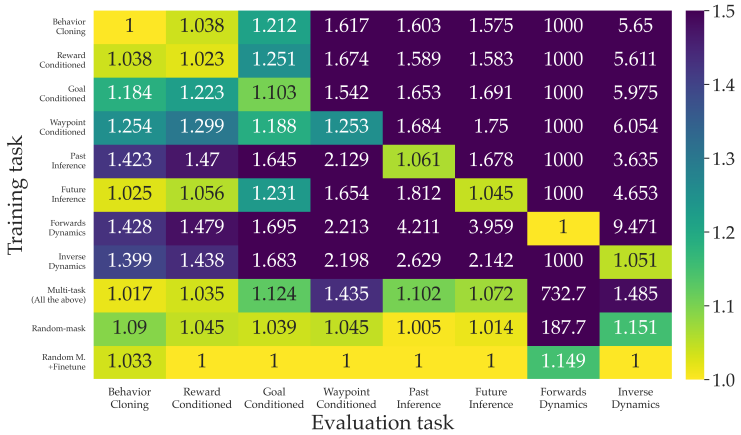

Figure 7: **Task-specific validation losses (normalized column-wise).** Each row corresponds to the performance of a single model evaluated in various ways, with the exception of the last row—for which each cell is fine-tuned on the respective evaluation task. Loss values are averaged across six seeds and then divided by the smallest value in each column. Thus, for each evaluation task (i.e., column), the best method has value 1; a value of 1.5 corresponds to a loss that is 50% higher than the best model in the column. Note that the performance of a multi-task model on the forwards dynamics task is particularly poor since the environment is deterministic: we should expect overfitting (with a single-task model) to perform the best. See Appendix A.5 for unnormalized values and more details.

results support **H1**: even if one is interested in a single inference task such as goal-conditioning, first training on multiple tasks generally improves performance.

Additionally, we find that `random-mask` leads to lower loss values on almost all evaluation tasks relative to `multi-task`, supporting **H2**: training on additional inference tasks beyond the specific ones of interest can further augment performance.

5 Trajectory Generation in a Complex Environment

In addition to gridworld, we also test our method in a partially observable, continuous-state and continuous-action environment, with a larger trajectory horizon (200 timesteps).

5.1 Environment Setup

We adapt the Mujoco-physics Maze2D environment [17] (see Figure 14), in which a point-mass object is placed at a random location in a maze, and is rewarded for moving towards a randomly generated target location (making this task "goal-conditioned by default").

Notably, we make this task harder than the original by: 1) removing the velocity information of the agent from each timestep's observation, and 2) increasing the amount of initial position randomization. These changes make the environment partially observable, forcing models trained on this data to implicitly infer the agent's velocity from observed context.

Expert dataset. We want our expert data to have some suboptimality so that reward-conditioning can be tested for better-than-demonstrator performance. We generate a dataset of expert trajectories by rolling out D4RL's PD controller (which is non-Markovian), and additionally add noise to the actions with zero-mean and 0.5 variance (which are then clipped to have each dimension between $-1, 1$). We generate 1000 trajectories of 200 timesteps, of which 900 are used for testing, and 100 for validation. More details on our adapted Maze2D environment and design decision can be found in Appendix A.7.

5.2 Models Trained

For the Maze2D evaluations, we focus on test-time reward performance on behavior cloning and offline RL (reward-conditioning) across various architectures and training regimes.

We consider Uni[MASK] models trained with the different training regimes: single-task, multi-task, random-mask, and finetune. We additionally consider other architectures, such as a feed-forward NN and Decision Transformer (DT) baselines [7]. We found that several of our design decisions for Uni[MASK] models – using positional encoding instead of timestep encoding, inputting the return-to-go token at the first timestep with the number of timesteps in the horizon – also improved GPT-based models like DT. We call our improved baseline Decision-GPT (for implementation details, see Appendix A.7). We train our Decision-GPT model with the single-task training regime. The only meaningful difference between Decision-GPT and a single-task Uni[MASK] model is whether the model is GPT- or BERT-based.

For each architecture and applicable training regime, we train separate models to perform behavior cloning and offline RL (reward-conditioning). The only exceptions are Uni[MASK] models trained with multi-task (trained to perform BC and RC) and random-mask. We train two sets of such models, for context lengths of 5 and 10 – meaning that during both training and evaluation, the models will respectively only be able to see the last 5 or 10 timsteps of the agent's interaction with the environment.

5.3 Results

We report reward evaluation results for 1000 rollouts in the Maze environment with standard errors across 5 seeds in Table 1.

The value of pre-training and fine-tuning for Uni[MASK] **models.** We find that fine-tuning is critical for good performance in more complex environments. We see that multi-task on performs comparably to single-task in behavior cloning and reward conditioning; however, random-mask in this setting suffers in terms of reward-performance. This suggests that multi-task training can be effective in increasing reward performance, but training on too many tasks can hurt out-of-the-box performance. However, finetune recovers the performance loss, again out-performing single-task (providing qualified support for **H1**). Surprisingly, fine-tuning multi-task does not improve performance as much as fine-tuning the randomly masked model, suggesting that specifically training on random masking provides benefits for adapting models to individual downstream tasks (providing qualified support for **H2**).

How do Uni[MASK] **models compare to other architectures?** For context length five, we see that finetune Uni[MASK] models perform better than all baselines we consider. However, increasing the context length to ten, we see that Uni[MASK] models performs poorly across the board, with finetune outperformed even by our Decision-GPT baseline. We speculate that this might be related to the documented difficulty of using BERT-like architectures (as that of Uni[MASK] models) for sequence generation [39].

Isolating the effect of GPT vs. BERT. In order to investigate the effect of using GPT-like architectures instead of BERT-like ones, we can consider the comparison between single-task Uni[MASK] and our Decision-GPT baseline: the main difference between these two models is only whether one uses BERT or GPT as the backbone of the architecture.[4] We find that while using GPT seems to yield similar performance to BERT for context length five, using GPT seems to give an advantage for longer sequence lengths. In particular, note that a larger context length enables GPT to increase performance, while this is not the case for single-task Uni[MASK]. This suggests that if one were able to use a GPT architecture and train it with random masking and fine-tuning, it might be possible to get the best of both worlds.

6 Limitations and Future Work

Comparison to other specialized models. We show that Uni[MASK] outperforms feedforward networks, Decision Transformer models, and for short sequence lengths also our own improved GPT-based baseline. However, we do not compare our models directly to different models in prior work that are specialized for specific tasks (e.g. goal-conditioning models, etc.). While this is a limitation of our work, it is also not our main focus: we propose a unifying framework for a variety of

[4] We additionally use input-stacking for Uni[MASK]—see Appendix A.3—but in preliminary experiments we found this to not affect performance.

Table 1: **Comparing among** Uni[MASK] **models**, we can isolate the benefit of random-mask: this training regime performs best across tasks and sequence lengths. **Comparing** single-task Uni[MASK] **to our Decision-GPT model**, we can isolate the effect of using a BERT-like architecture vs. a GPT-like architecture: for larger context lengths, we see that BERT-like models struggle to maintain the same generation quality, while our Decision-GPT model is able to make use of the extra context effectively. Every entry in the table corresponds to separate training runs (trained on either BC or RC), except for the cells denoted with †, which are shared across tasks (but not sequence lengths).

	Ctx. len 5		Ctx. len 10	
Model	BC	RC	BC	RC
Uni[MASK] **Models**				
Uni[MASK] - single-task	$2.71 \pm .02$	$2.63 \pm .02$	$2.50 \pm .03$	$2.42 \pm .04$
Uni[MASK] - multi-task (BC & RC)	$2.71 \pm .01^\dagger$	$2.71 \pm .02^\dagger$	$2.48 \pm .03^\dagger$	$2.47 \pm .04^\dagger$
Uni[MASK] - multi-task + finetune	$2.72 \pm .05$	$2.72 \pm .02$	$2.45 \pm .05$	$2.46 \pm .06$
Uni[MASK] - random-mask	$2.11 \pm .06^\dagger$	$2.14 \pm .09^\dagger$	$2.29 \pm .08^\dagger$	$2.30 \pm .08^\dagger$
Uni[MASK] - finetune	$\mathbf{2.74 \pm .06}$	$\mathbf{2.73 \pm .04}$	$\mathbf{2.67 \pm .04}$	$\mathbf{2.64 \pm .05}$
Other architectures				
Feedforward Neural Network	$1.62 \pm .05$	$1.60 \pm .05$	$1.82 \pm .07$	$1.83 \pm .05$
Decision Transformer [7]	$1.33 \pm .03$	$1.50 \pm .04$	$1.99 \pm .02$	$1.76 \pm .04$
Our Decision-GPT model	$2.61 \pm .01$	$2.35 \pm .03$	$\mathbf{2.75 \pm .02}$	$\mathbf{2.74 \pm .02}$

tasks in sequential decision problems, and extensively analyze how different training regimes affect performance.

Longer context lengths. One limitation in our experimentation are the relatively short context lengths used. As we saw in our experiments, using longer context lengths starts affecting Uni[MASK] models' performance negatively. In part, this could be addressed by designing masking schemes tailed to specific test-time tasks (see Appendix A.2), or using principled masking schemes [26]. However, this degradation may be attributed to our use of a BERT-like (rather than GPT-like) architecture, which seems less compatible with longer sequence lengths. A clear avenue of future work would therefore be to get the "best of both worlds": long sequences and benefits of random-mask pre-training by using a GPT-like architectures, with our random-mask and finetune training regimes. This which would require finding ways to make GPT act like a bidirectional model – for which recent methods in NLP might offer a useful starting point [1, 16].

Other future work. Another exciting direction for future work is trying to see whether the benefits obtained from random-mask (or even multi-task) would also apply to other types of inferences (e.g. Bayes Networks more generally); alternatively, even trivially extending the approach to multi-agent settings (for which token-stacking could prove more valuable), could enable many interesting masking-enabled queries [28].

7 Conclusion

Broader impacts. The prospect of very large "foundation models" [2] becoming the norm for sequential problems (in addition to language) raises concerns, in that it de-democratizes development and usage [24]. We do use significantly smaller models and computational power than similar work, leaving open the option to have more modestly-sized environment-specific foundation models. However, we acknowledge that this works still encourages this problematic trend.

Summary. In this work we propose Uni[MASK], a framework for flexibly defining and training models which: **1)** are naturally able to represent any inference task and support multi-task training in sequential decision problems, **2)** match or surpass the performance of single-task models after multi-task pre-training, and almost always surpasses them after fine-tuning. We believe our approach provides an elegant conceptual formulation and exciting experimental results which warrant further investigation by the research community.

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Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes] See Section 6.
   (c) Did you discuss any potential negative societal impacts of your work? [Yes] See Section 7.
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [N/A]
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3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes] The code is linked at the top of the Appendix.
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] See the relevant Appendix sections, for each environment and model.
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes] Yes, with the exception of Figure 7. More details in Appendix A.5

(d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes] See Appendix.

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