SIMULATING ACTION DYNAMICS WITH NEURAL PROCESS NETWORKS

Anonymous authors
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ABSTRACT

Understanding procedural language requires anticipating the causal effects of actions, even when they are not explicitly stated. In this work, we introduce Neural Process Networks to understand procedural text through (neural) simulation of action dynamics. Our model complements existing memory architectures with dynamic entity tracking by explicitly modeling actions as state transformers. The model updates the states of the entities by executing learned action operators. Empirical results demonstrate that our proposed model can reason about the unstated causal effects of actions, allowing it to provide more accurate contextual information for understanding and generating procedural text, all while offering more interpretable internal representations than existing alternatives.

1 INTRODUCTION

Understanding procedural text such as instructions or stories requires anticipating the implicit causal effects of actions on entities. For example, given instructions such as "*add* blueberries to the muffin mix, then *bake* for one half hour," an intelligent agent must be able to anticipate a number of entailed facts (e.g., the blueberries are now in the oven; their "temperature" will increase). While this common sense reasoning is trivial for humans, most natural language understanding algorithms do not have the capacity to reason about causal effects not mentioned directly in the surface strings (Levy et al., 2015; Jia & Liang, 2017; Lucy & Gauthier, 2017).

In this paper, we introduce Neural Process Networks, a procedural language understanding system that tracks common sense attributes through neural simulation of action dynamics. Our network models interpretation of natural language instructions as a *process* of actions and their cumulative effects on entities. More concretely, reading one sentence at a time, our model attentively selects what actions to execute on which entities, and remembers the state changes induced with a recurrent memory structure. In Figure 1, for example, our model indexes the "tomato" embedding, selects the "wash" and "cut" functions and performs a computation that changes the "tomato" embedding so that it can reason about attributes such as its "SHAPE" and "CLEANLINESS".

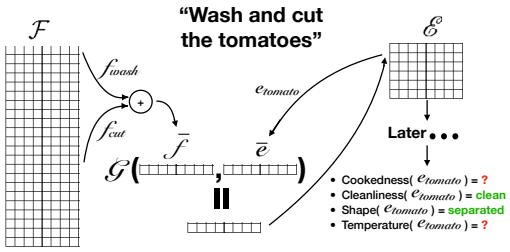

Figure 1: The *process* is a narrative of entity state changes induced by actions. In each sentence, these state changes are induced by simulated actions and must be remembered.

Our model contributes to a recent line of research that aims to model aspects of world state changes, such as language models and machine readers with explicit entity representations (Henaff et al., 2016; Yang et al., 2016; Ji et al., 2017), as well as other more general purpose memory network variants (Weston et al., 2014; Sukhbaatar et al., 2015; Hill et al., 2015; Seo et al., 2016). This *world-centric* modeling of procedural language (i.e., understanding by simulation) abstracts away from the surface strings, complementing *text-centric* modeling of language, which focuses on syntactic and semantic labeling of surface words (i.e., understanding by labeling).

Unlike previous approaches, however, our model also learns explicit action representations as functional operators (See Figure 1). While representations of action semantics could be acquired through an embodied agent that can see and interact with the world (Oh et al., 2015), we propose to learn these representations from text. In particular, we require the model to be able to *explain* the causal effects of actions by predicting natural language attributes about entities such as "LOCATION" and "TEMPERATURE". The model adjusts its representations of actions based on errors it makes in predicting the resultant state changes to attributes. This textual simulation allows us to model aspects of action causality that are not readily available in existing simulation environments. Indeed, most virtual environments offer limited aspects of the world – with a primary focus on spatial relations (Oh et al., 2015; Chiappa et al., 2017; Wahlstrom et al., 2015). They leave out various other dimensions of the world states that are implied by diverse everyday actions such as "dissolve" (change of "COMPOSITION") and "wash" (change of "CLEANLINESS").

Empirical results demonstrate that parametrizing explicit action embeddings provides an inductive bias that allows the neural process network to learn more informative context representations for understanding and generating natural language procedural text. In addition, our model offers more interpretable internal representations and can reason about the unstated causal effects of actions explained through natural language descriptors. Finally, we include a new dataset with fine-grained annotations on state changes, to be shared publicly, to encourage future research in this direction.

2 NEURAL PROCESS NETWORK

The neural process network is an interpreter that reads in natural language sentences, one at a time, and simulates the process of actions being applied to relevant entities through learned representations of actions and entities.

2.1 OVERVIEW AND NOTATION

The main component of the neural process network is the simulation module (§2.5), a recurrent unit whose internals simulate the effects of actions being applied to entities. A set of V actions is known a priori and an embedding is initialized for each one, $\mathcal{F} = \{f_1, ...f_V\}$. Similarly, a set of I entities is known and an embedding is initialized for each one: $\mathcal{E} = \{e_1, ...e_I\}$. Each e_i can be considered to encode information about state attributes of that entity, which can be extracted by a set of state predictors (§2.6). As the model reads text, it "applies" action embeddings to the entity vectors, thereby changing the state information encoded about the entities.

For any document d, an initial list of entities I_d is known and $\mathcal{E}_d = \{e_i | i \in I_d\} \subset \mathcal{E}$ entity state embeddings are initialized. As the neural process network reads a sentence from the document, it selects a subset of both $\mathcal{F}$ (§2.3) and $\mathcal{E}_d$ (§2.4) based on the actions performed and entities affected in the sentence. The entity state embeddings are changed by the action and the new embeddings are used to predict end states for a set of state changes (§2.6). The prediction error for end states is backpropagated to the action embeddings, learning action representations that model the simulation of desired causal effects on entities. This process is broken down into five modules below. Unless explicitly defined, all W and b variables are parametrized linear projections and biases. We use the notation $\{e_i\}_t$ when referring to the values of the entity embeddings before processing sentence s_t.

2.2 SENTENCE ENCODER

Given a sentence s_t, a Gated Recurrent Unit (Cho et al., 2014) encodes each word and outputs its last hidden vector as a sentence encoding h_t (Sutskever et al., 2014).

2.3 ACTION SELECTOR

Given h_t from the sentence encoder, the action selector (bottom left in Fig. 2) contextually determines which action(s) from $\mathcal{F}$ to execute. For example, if the input sentence is *"wash and cut beets"*, both f_{wash} and f_{cut} must be selected. To account for multiple actions, we make a soft

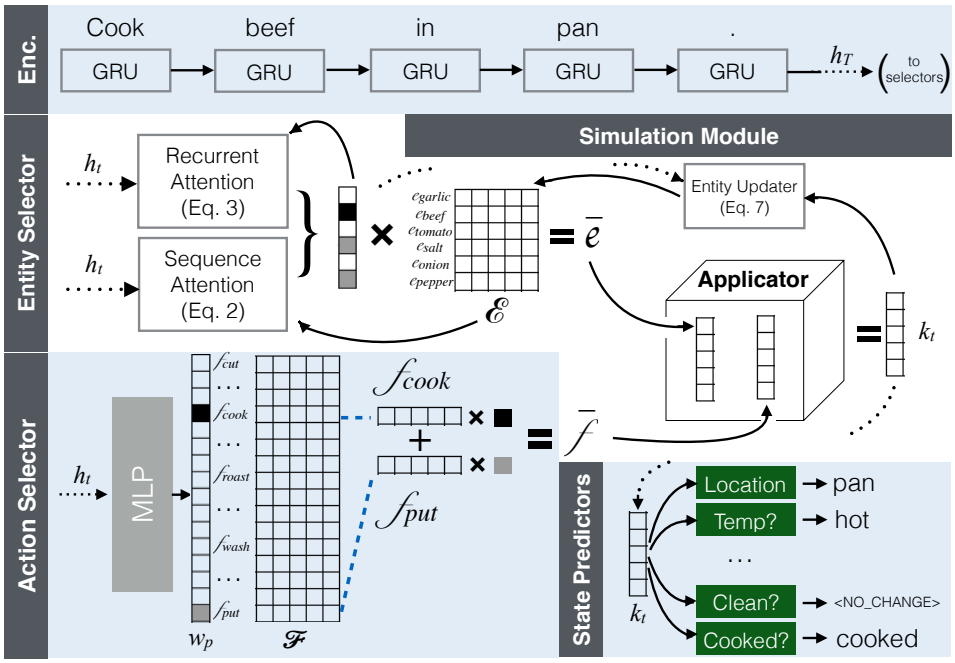

Figure 2: Model Summary. The sentence encoder converts a sentence to a vector representation, h_t. The action selector and entity selector use the vector representation to choose the actions that are applied and the entities that are acted upon in the sentence. The simulation module indexes the action and entity state embeddings, and applies the transformation to the entities. The state predictors predict the new state of the entities if a state change has occurred. Equation references are provided in parentheses.

selection over $\mathcal{F}$, yielding a weighted sum of the selected action embeddings $\bar{f}_t$:

$$\begin{aligned} w_p &= \text{MLP}(h_t) \\ \bar{w}_p &= \frac{w_p}{\sum_{j=1}^{V} w_{p_j}} \\ \bar{f}_t &= \bar{w}_p^\intercal \mathcal{F} \end{aligned} \tag{1}$$

where MLP is a parametrized feed-forward network with a sigmoid activation and $w_p \in \mathbb{R}^V$ is the attention distribution over V possible actions (§3.1). We compose the action embedding by taking the weighted average of the selected actions.

2.4 Entity Selector

Sentence Attention Given h_t from the sentence encoder, the entity selector chooses relevant entities using a soft attention mechanism:

$$\begin{aligned} \tilde{h}_t &= \text{ReLU}(W_1 h_t + b_1) \\ d_i &= \sigma(e_{i_0}^\intercal W_2 [\tilde{h}_t; w_p]) \end{aligned} \tag{2}$$

where W_2 is a bilinear mapping, e_{i_0} is a unique key for each entity (§2.5), and d_i is the attention weight for entity embedding e_i. For example, in *"wash and cut beets and carrots"*, the model should select e_{beet} and e_{carrot}.

Recurrent Attention While sentence attention would suffice if entities were always explicitly mentioned, natural language often elides arguments or uses referent pronouns. As such, the module must be able to consider entities mentioned in previous sentences. Using $\tilde{h}_t$, the model computes a soft choice over whether to choose affected entities from this step's attention d_i or the previous step's attention distribution.

$$\begin{aligned} c &= softmax(W_3 \tilde{h}_t + b_3) \\ a_{i_t} &= c_1 d_i + c_2 a_{i_{t-1}} + c_3 \mathbf{0} \end{aligned} \tag{3}$$

where $c \in \mathbb{R}^3$ is the choice distribution, $a_{i_{t-1}}$ is the previous sentence's attention weight for each entity, a_{i_t} is the final attention for each entity, and $\mathbf{0}$ is a vector of zeroes (providing the option to not change any entity). Prior entity attentions can propagate forward for multiple steps.

2.5 SIMULATION MODULE

Entity Memory A unique state embedding e_i is initialized for every entity i in the document. A unique key to index each embedding e_{i_0} is set as the initial value of the embedding (Henaff et al., 2016; Miller et al., 2016). After the model reads s_t, it modifies $\{e_i\}_t$ to reflect changes influenced by actions. At every time step, the entity memory receives the attention weights from the entity selector, normalizes them and computes a weighted average of the relevant entity state embeddings:

$$\alpha_i = \frac{a_i}{\sum_{j=1}^{I_d} a_j} \quad (4) \qquad \bar{e}_t = \sum_{j=1}^{I_d} \alpha_i e_i \quad (5)$$

Applicator Given the action summary embedding $\bar{f}_t$ and the entity summary embedding $\bar{e}_t$, the applicator (middle right in Fig. 2) applies the selected actions to the selected entities, and outputs the new proposal entity embedding k_t.

$$k_t = \text{ReLU}(\bar{f}_t W_4 \bar{e}_t + b_4) \quad (6)$$

where W_4 is a third order tensor projection. The vector k_t is the new representation of the entity $\bar{e}_t$ after the applicator simulates the action being applied to it.

Entity Updater The entity updater interpolates the new proposal entity embedding k_t and the set of current entity embeddings $\{e_i\}_t$:

$$e_{i_{t+1}} = a_{i_t} k_t + (1 - a_{i_t}) e_{i_t} \quad (7)$$

yielding an updated set of entity embeddings $\{e_i\}_{t+1}$. Each embedding is updated proportional to its entity's unnormalized attention a_i, allowing the model to completely overwrite the state embedding for any entity. For example, in the sentence *"mix the flour and water,"* the embeddings for e_{flour} and e_{water} must both be overwritten by k_t because they no longer exist outside of this new composition.

2.6 STATE PREDICTORS

Given the new proposal entity embedding k_t, the state predictor (bottom right in Fig. 2) predicts changes to the resulting entity embedding k_t along the following six dimensions: location, cookedness, temperature, composition, shape, and cleanliness. Discrete multi-class classifiers, one for each dimension, take in k_t and predict a unique end state for their corresponding state change type:

$$P(Y_s|k_t) = softmax(W_s k_t + b_s) \quad (8)$$

For location changes, which require contextual information to predict the end state, k_t is concatenated with the original sentence representation h_t to predict the final state.

3 TRAINING

3.1 STATE CHANGE KNOWLEDGE

In this work we focus on physical action verbs in cooking recipes. We manually collect a set of 384 actions such as *cut, bake, boil, arrange*, and *place*, organizing their causal effects along the following predefined dimensions: LOCATION, COOKEDNESS, TEMPERATURE, SHAPE, CLEANLINESS and COMPOSITION. The textual simulation operated by the model induces state changes along these dimensions by applying actions functions from the above set of 384. For example, *cut* entails a change in SHAPE, while *bake* entails a change in TEMPERATURE, COOKEDNESS, and even LOCATION. We annotate the state changes each action induces, as well as the end state of the action, using Amazon Mechanical Turk. The set of possible end states for a state change can range from 2 for binary state changes to more than 200 (See Appendix C for details). Table 1 provides examples of annotations in this action lexicon.

Action	State Change Types	End States
braise	COOKEDNESS; TEMPERATURE	COOKED; HOT
chill	TEMPERATURE	COLD
knead	SHAPE	MOLDED
wash	CLEANLINESS	CLEAN
dissolve	COMPOSITION	COMPOSED
refrigerate	TEMPERATURE; LOCATION	COLD; REFRIGERATOR
slice	SHAPE	SEPARATED

Table 1: Example actions, the state changes they induce, and the possible end states

3.2 DATASET

For learning and evaluation, we use a subset of the Now You're Cooking dataset (Kiddon et al., 2016). We chose 65816 recipes for training, 175 recipes for development, and 700 recipes for testing. For the development and test sets, crowdsourced workers densely annotate actions, entities and state changes that occur in each sentence so that we can tune hyperparameters and evaluate on gold evaluation sets. Annotation details are provided in Appendix C.3.

3.3 COMPONENT-WISE TRAINING

The neural process network is trained by jointly optimizing multiple losses for the action selector, entity selector, and state change predictors. Importantly, our training scheme uses weak supervision because dense annotations are prohibitively expensive to acquire at a very large scale. Thus, we heuristically extract verb mentions from each recipe step and assign a state change label based on the state changes induced by that action (§3.1). Entities are extracted similarly based on string matching between the instructions and the ingredient list. We use the following losses for training:

Action Selection Loss Using noisy supervision, the action selector is trained to minimize the cross-entropy loss for each possible action, allowing multiple actions to be chosen at each step if multiple actions are mentioned in a sentence. The MLP in the action selector (Eq. 1) is pretrained.

Entity Selection Loss Similarly, to train the attentive entity selector, we minimize the binary cross-entropy loss of predicting whether each entity is affected in the sentence.

State Change Loss For each state change predictor, we minimize the negative loglikelihood of predicting the correct end state for each state change.

Coverage Loss An underlying assumption in many narratives is that all entities that are mentioned should be important to the narrative. We add a loss term that penalizes narratives whose combined attention weights for each entity does not sum to more than 1.

$$\mathcal{L}_{cover} = -\frac{1}{I_d} \sum_{i=1}^{I_d} \log \sum_{t=1}^{S} a_{i_t} \tag{9}$$

where a_{i_t} is the attention weight for a particular entity at sentence t and I_d is the number of entities in a document. $\sum_{t=1}^{S} a_{i_t}$ is upper bounded by 1. This is analogous to the coverage penalty used in neural machine translation (Tu et al., 2016).

4 EXPERIMENTAL SETUP

We evaluate our model on two tasks: tracking and generation, and provide a qualitative analysis of the internal workings of our model.

4.1 TRACKING

In the tracking task, we evaluate the model's ability to identify which entities are selected and what changes have been made to them in every step. We break the tracking task into two separate evaluations, entity selection and end state prediction.

Model	Entity Selection			State Change	
	F1	UR	CR	F1	ACC
Adapted Gated Recurrent Unit	45.94	67.69	7.74	41.16	52.59
Adapted Recurrent Entity Network	48.57	71.88	9.87	42.32	53.47
No Recurrent Attention (Eq. 3)	48.91	72.32	12.67	42.14	50.48
No Coverage Loss (Eq. 9)	55.18	73.98	20.23	44.44	**55.20**
No Action Connections (Eq. 2)	54.85	73.54	20.03	44.05	54.81
Full Model	**55.39**	**74.88**	**20.45**	**44.65**	55.07

Table 2: Results for entity selection and state change selection

Metrics In the entity selection test, we report the F1 score of choosing the correct entities in any step. A selected entity is defined as one whose attention weight a_i is greater than 50% (§2.4). Because entities may be harder to predict when they have been combined with other entities (e.g., the mixture may have a new name), we also report the recall for selecting combined (CR) and uncombined (UR) entities. In the end state prediction test, we report how often the model correctly predicts the state change performed in a recipe step and the resultant end state. This score is then scaled by the accuracy of predicting which entities were changed in that same step. We report the average F1 and accuracy across the six state change types.

Baselines We compare our models against two baselines. First, we built a GRU model that is trained to predict entities and state changes independently. This can be viewed as a bare minimum network with no action representations or recurrent entity memory. The second baseline is a Recurrent Entity Network (Henaff et al., 2016) with changes to fit our task. First, the model can tie memory cells to a subset of the full list of entities so that it only considers entities that are present in a particular recipe. Second, the entity distribution for writing to the memory cells is re-used when we query the memory cells. The normalized weighted average of the entity cells is used as the input to the state predictors. The unnormalized attention when writing to each cell is used to predict selected entities. Both baselines are trained with entity selection and state change losses (§3.3).

Ablations We report results on three ablations. In the first ablation, we remove the recurrent attention (Eq. 3). The model only predicts entities using the current encoder hidden state. In the second ablation, the model is trained with no coverage penalty for not using all entities (Eq. 9). In the final ablation, we prune the connection from the action selector w_p to the entity selector (Eq. 2).

4.2 GENERATION

The generation task tests whether our system can produce the next step in a recipe based on the previous steps that have been performed. The model is provided all of the previous steps as context and must generate the following sentence.

Metrics We report the combined BLEU score and ROUGE score of the generated sequence relative to the reference sequence. Each candidate sequence has one reference sentence. Both metrics are computed at the corpus-level. Also reported are "VF1", the F1 score for the overlap of the actions performed in the reference sequence and the verbs mentioned in the generated sequence, and "SF1", the F1 score for the overlap of end states annotated in the reference sequence and predicted by the generated sequences. End states for the generated sequences are extracted using the lexicon from Section 3.1 based on the actions performed in the sentence.

Baselines For the generation task, we use three baselines: a seq2seq model with no attention (Sutskever et al., 2014), an attentive seq2seq model (Bahdanau et al., 2014), and the neural checklist model (Kiddon et al., 2016). Implementation details for baselines can be found in Appendix B.

Setup To apply our model to the task of recipe step generation, we input the context sentences through the neural process network and record the entity state vectors once the entire context has been read (§2.5). These vectors can be viewed as a snapshot of the current state of the entities once the preceding context has been simulated inside the neural process network. We encode these vectors using a bidirectional GRU (Cho et al., 2014) and take the final time step hidden state $\mathbb{e}_I$. A different GRU encodes the context words in the same way (yielding $\mathbb{h}_T$) and the first hidden state input to the decoder is computed using the projection function:

Good	s_{t-1}	Add tomato paste, broth, garlic, chili powder, cumin, chile peppers, and water.
	s_t	Bring to boil, then turn very low, cover and simmer until meat is tender.
	selected	meat, garlic, chili powder, tomato paste, cumin, chiles, beef broth, water
	correct	Same + [oil]
Good	s_{t-4}	Stir in oats, sugar, flour, corn syrup, milk, vanilla extract, and salt.
	s_{t-3}	Mix well.
	s_{t-2}	Drop by measuring teaspoonfuls onto cookie sheets.
	s_{t-1}	Bake 5 - 7 minutes.
	s_t	Let cool.
	selected	oats, sugar, flour, corn syrup, milk, vanilla extract, salt
	correct	oats, sugar, flour, corn syrup, milk, vanilla extract, salt
Good	s_{t-1}	In a large saucepan over low heat, melt marshmallows.
	s_t	Add sprinkles, cereal, and raisins, stir until well coated.
	selected	marshmallows, cereal, raisins
	correct	marshmallows, cereal, raisins, sprinkles
Bad	s_{t-3}	Ladle the barbecue sauce around the crust and spread.
	s_{t-2}	Add mozzarella, yellow cheddar, and monterey jack cheese.
	s_{t-1}	Next, add onion mixture and sliced chicken breast .
	s_t	Top pizza with jalapeno peppers.
	selected	jalapenos
	correct	crust, sauce, mozzarella, cheddar, monterey jack, white onion, chicken, jalapenos
Bad	s_{t-2}	Combine 1 cup flour, salt, and 1 tbsp sugar.
	s_{t-1}	Cut in butter until mixture is crumbly, then sprinkle with vinegar .
	s_t	Gather dough into a ball and press into bottom of 9 inch springform pan.
	selected	butter, vinegar
	correct	flour, salt, sugar, butter, vinegar

Table 3: Examples of the model selecting entities for sentence s_t. The previous sentences are provided as context in cases where they are relevant.

$$\tilde{h}_0 = W_5(\mathbb{e}_I \circ \mathbb{h}_T) \tag{10}$$

where $\circ$ is the Hadamard product between the two encoder outputs. All models are trained by minimizing the negative loglikelihood of predicting the next word for the full sequence. Implementation details can be found in Appendix A.

5 Experimental Results

5.1 Tracking

Entity Selection Tracking As shown in Table 2, our full model greatly outperforms all baselines at selecting entities, with an F1 score of 55.39%. The ablation study shows that the recurrent attention, coverage loss, and action connections improve performance. Our success at predicting entities extends to both uncomposed entities, which are still in their raw forms (e.g., melt the *butter* $\rightarrow$ butter), and composed entities, in which all of the entities that make up a composition must be selected. For example, in a *Cooking lasagna* recipe, if the final step involves baking the prepared lasagna, the model must select all the entities that make up the lasagna (e.g., lasagna sheets, beef, tomato sauce). In Table 3, we provide examples of our model's capabilities for handling complex cases such as compositional entities (Ex. 1, 3), and elided arguments over long time windows (Ex. 2). We also provide examples where the model fails to select the correct entities because it does not identify the mapping between a reference construct such as "pizza" (Ex. 4) or "dough" (Ex. 5) and the set of entities that composes it, indicating the difficult of selecting the full set for a composed entity.

State Change Tracking In Table 2, we show that our full model outperforms competitive baselines such as Recurrent Entity Networks (Henaff et al., 2016) and jointly trained GRUs. While the ablation without the coverage loss shows higher accuracy, we attribute this to the fact that it predicts a smaller number of total state changes.

Action	Nearest Neighbor Actions
cut	slice, split, snap, slash, carve, slit, chop
boil	cook, microwave, fry, steam, simmer
add	sprinkle, mix, reduce, splash, stir, dust
wash	rinse, scrub, refresh, soak, wipe, scale
mash	spread, puree, squeeze, liquefy, blend
place	ease, put, lace, arrange, leave
rinse	wash, refresh, soak, wipe, scrub, clean
warm	reheat, ignite, heat, light, crisp, preheat
steam	microwave, crisp, boil, parboil, heat
sprinkle	top, pat, add, dip, salt, season
grease	coat, rub, dribble, spray, smear, line

Table 4: Most similar actions based on cosine similarity of action embeddings

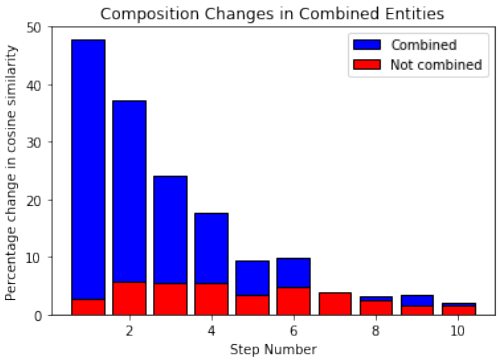

Figure 3: Change in cosine similarity of entity state embeddings

Model	BLEU-4	ROUGE-L	VF1	SF1
Vanilla Seq2Seq	2.80	32.67	15.76	38.20
Attentive Seq2Seq	2.58	34.53	15.72	36.65
Neural Checklist	2.66	35.07	17.33	37.25
NPN Generator	**3.73**	**35.35**	**17.51**	**40.32**

Table 5: Generation Results

5.2 Action Embeddings and Compositionality

Action Embeddings In our model, each action is assigned its own embedding, but many actions induce similar changes in the physical world (e.g.,"cut" and "slice"). After training, we compute the pairwise cosine similarity between each pair of action embeddings. In Table 4, we see that actions that perform similar functions are neighbors in embedding space, indicating the model has captured certain semantic properties of these actions. Learning action representations through the state changes they induce has allowed the model to cluster actions by their transformation functions.

Entity Compositions When individual entities are combined into new constructs, our model averages their state embeddings (Eq. 5), applies an action embedding to them (Eq. 6), and writes them to memory (Eq. 7). The state embeddings of entities that are combined should be overwritten by the same new embedding. In Figure 3, we present the percentage increase in cosine similarity for state embeddings of entities that are combined in a sentence (blue) as opposed to the percentage increase for those that are not (red bars). While the soft attention mechanism for entity selection allows similarities to leak between entity embeddings, our system is generally able to model the compositionality patterns that result from entities being combined into new constructs.

5.3 Recipe Generation

Results Our results in Table 5 indicate that sequences generated using the neural process network entity states as additional input yield higher scores than competitive baselines. The entity states allow the model to predict next steps conditioned on a representation of the world being simulated by the neural process network. Additionally, the higher VF1 and SF1 scores indicate that the model is indeed using the extra information to better predict the actions that should follow the context provided. Examples from the dev set are provided in Table 6, showing that the NPN generator can use information about ingredient states to reason about the most likely next step. The first example is particularly interesting as it contrasts the generation from the NPN-aware model, which learns to condition on entity states (knowing that raw butter will likely be melted) with the generation from the Neural Checklist (Kiddon et al., 2016), which learns to condition on entity usage (using the bourbon, salt, pepper and thyme). The third example is also interesting because the model learns an incorrect correspondence of draining cooked vegetables such as squash, even if it is not relevant to this recipe because the squash is steamed. The seq2seq baselines, meanwhile, output reasonable sentences given the immediate context, but do not exhibit understanding of global patterns.

Context	Preheat oven to 425 degrees.
Reference	Melt butter in saucepan and mix in bourbon, thyme, pepper, and salt.
NPN	Melt butter in skillet.
Seq2seq	Lightly grease 4 x 8 baking pan with sunflower oil.
Attentive Seq2seq	Combine all ingredients and mix well.
Neural Checklist	In a large mixing bowl, combine bourbon, salt, pepper and thyme.
Context	Pour egg mixture over caramelized sugar in cake pan. Place cake pan in large shallow baking dish. Bake for 55 minutes or until knife inserted into flan comes out clean.
Reference	Cover and chill at least 8 hours.
NPN	Refrigerate until ready to use.
Seq2seq	Serve at room temperature.
Attentive Seq2seq	Store in an airtight container.
Neural Checklist	Meanwhile, combine sugar, coffee and egg yolks.
Context	Cut squash into large pieces and steam. Remove cooked squash from shells;
Reference	Measure 4 cups pulp and reserve remainder for another dish.
NPN	Drain.
Seq2seq	Mash pulp with a fork.
Attentive Seq2seq	Set aside.
Neural Checklist	Reserve 2 cups of cooking liquid.

Table 6: Examples of the model generating sentences compared to baselines. The context and reference are provided first, followed by our model's generation and then the baseline generations

6 Related Work

Recent studies in machine comprehension have used a neural memory component to store a running representation of processed text (Weston et al., 2014; Sukhbaatar et al., 2015; Hill et al., 2015; Seo et al., 2016). While these approaches map text to memory vectors using standard neural encoder approaches, our model, in contrast, directly interprets text in terms of the effects actions induce in entities, providing an inductive bias for learning how to represent stored memories. More recent work in machine comprehension also sought to couple the memory representation with tracking entity states (Henaff et al., 2016). Our work seeks to provide a relatively more structured representation of domain-specific action knowledge to provide an inductive bias to the reasoning process.

Neural Programmers (Neelakantan et al., 2015; 2016) have also used functions to simulate reasoning, by building a model to select rows in a database and applying operation on those selected rows. While their work explicitly defined the effect of a number of operations for those rows, we provide a framework for learning representations for a more expansive set of actions, allowing the model to learn representations for how actions change the state space.

Works on instructional language studied the task of building discrete graph representations of recipes using probabilistic models (Kiddon et al., 2015; Mori et al., 2014; 2012). We propose a complementary new model by integrating action and entity relations into the neural network architecture and also address the additional challenge of tracking the state changes of the entities.

Additional work in tracking states with visual or multimodal context has focused on 1) building graph representations for how entities change in goal-oriented domains (Gao et al., 2016; Liu et al., 2016; Si et al., 2011) or 2) tracking visual state changes based on decisions taken by agents in environment simulators such as videos or games (Chiappa et al., 2017; Wahlstrom et al., 2015; Oh et al., 2015). Our work, in contrast, models state changes in embedding space using only text-based signals to map real-world actions to algebraic transformations.

7 Conclusion

We introduced the *Neural Process Network* for modeling a process of actions and their causal effects on entities by learning action transformations that change entity state representations. The model maintains a recurrent memory structure to track entity states and is trained to predict the state changes that entities undergo. Empirical results demonstrate that our model can learn the causal effects of action semantics in the cooking domain and track the dynamic state changes of entities, showing advantages over competitive baselines.

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A TRAINING DETAILS OF OUR FULL MODEL AND ABLATIONS

A.1 TRACKING MODELS

The hidden size of the instruction encoder is 100, the embedding sizes of action functions and entities are 30. We use dropout with a rate of 0.3 before any non-recurrent fully connected layers Srivastava et al. (2014). We use the Adam optimizer (Kingma & Ba, 2014) with a learning rate of .001 and decay by a factor of 0.1 if we see no improvement on validation loss over a single epoch. We stop training early if the development loss does not decrease for five epochs. The batch size is 64. We use two instruction encoders, one for the entity selector, and one for the action selector. Word embeddings and entity embeddings are initialized with skipgram embeddings (Mikolov et al., 2013a;b) using a word2vec model trained on the training set. We use a vocabulary size of 7358 for words, and 2996 for entities.

A.2 GENERATION MODEL

The hidden size of the context encoder is 200. The hidden size of the state vector encoder is 200. State vectors have dimensionality 30 (the same as in the neural process network). Dropout of 0.3 is used during training in the decoder. The context and state representations are projected jointly using an element-wise product followed by a linear projection Kim et al. (2016). Both encoders and the decoder are single layer. The learning rate is 0.0003 initially and is halved every 5 epochs. The model is trained with the Adam optimizer.

B TRAINING DETAILS OF BASELINES

B.1 TRACKING BASELINES

Joint Gated Recurrent Unit The hidden state of the GRU is 100. We use a dropout with a rate of 0.3 before any non-recurrent fully connected layers. We use the Adam optimizer with a learning rate of .001 and decay by a factor of 0.1 if we see no improvement on validation loss over a single epoch. We stop training early if the development loss does not decrease for five epochs. The batch size is 64. We use encoders, one for the entity selector, and one for the state change predictors. Word embeddings are initialized with skipgram embeddings using a word2vec model trained on the training set. We use a vocabulary size of 7358 for words.

Recurrent Entity Networks Memory cells are tied to the entities in the document. For a recipe with 12 ingredients, 12 entity cells are initialized. All hyperparameters are the same as the in the bAbI task from Henaff et al. (2016). The learning rate start at 0.01 and is halved every 25 epochs. Entity cells and word embeddings are 100 dimensional. The encoder is a multiplicative mask initialized the same as in Henaff et al. (2016). Intermediate supervision from the weak labels is provided to help predict entities. A separate encoder is used for computing the attention over memory cells and the content to write to the memory. Dropout of 0.3 is used in the encoders. The batch size is 64. We use a vocabulary size of 7358 for words, and 2996 for entities.

B.2 GENERATION BASELINES

Seq2seq The hidden size of the GRU encoder and decoder is 200. A single layer is used for both the encoder and decoder. Dropout of 0.3 is used during training in the decoder. We use the Adam optimizer, a starting learning rate 0.0003, which is halved every 5 epochs. and multiply the learning rate by 0.1 every 5 epochs. The encoder is bidirectional. The model is trained to minimize the negative loglikelihood of predicting the next word.

Attentive Seq2seq The encoder is the same as in the seq2seq baseline. A multiplicative attention between the decoder hidden state and the context vectors is used to compute the attention over the context at every decoder time step. The model is trained with the same learning rate, learning schedule and loss function as the seq2seq baseline.

Neural Checklist We use a pretained model from Kiddon et al. (2016). The hidden state of the model is 256-dimensional. Parameters are uniformly initialized between -0.35 and 0.35. A learning rate of 0.1 is used for training and the model is trained with stochastic gradient descent. A batch size of 30 is used for training. The neural checklist is trained to generate a full recipe, while our task involves just generating the next step in a recipe provided a set of preceding sentences. We input the full context into the neural checklist, allowing it to update its internals and then make it start generating when we reach the end of the context.

C ANNOTATIONS

C.1 ANNOTATING STATE CHANGES

We provide workers with a verb, its definition, an illustrative image of the action, and a set of sentences where the verb is mentioned. Workers are provided a checklist of the six state change types and instructed to identify which of them the verb causes. They are free to identify multiple changes. Seven workers annotate each verb and we assign a state change based on majority vote. Of the set of 384 verbs extracted, only 342 have a state change type identified with them. Of those, 74 entail multiple state change types.

C.2 ANNOTATING END STATES

We give workers a verb, a state change type, and an example with the verb and ask them to provide an end state for the ingredient the verb is applied to in the example. We then use the answers to manually aggregate a set of end states for each state change type. These end states are used as labels when the model predicting state changes. For example, a LOCATION change might lead to an end state of "pan," "pot", or "oven." End states for each state change type are provided in Table 7.

State Change Type	End States
Temperature	hot; cold; room
Composition	composed; not composed
Cleanliness	clean; dirty; dry
Cookedness	cooked; raw
Shape	molded; hit; deformed; separated
Location	pan, pot, cupboard, screen, scale, garbage, 260 more

Table 7: End states for each state change type

C.3 ANNOTATING DEVELOPMENT AND TEST SETS

Annotators are instructed to note any entities that undergo one of the six state changes in each step, as well as to identify new combinations of ingredients that are created. For example, the sentence "Cut the tomatoes and add to the onions" would involve a SHAPE change for the tomatoes and a combination created from the "tomatoes" and "onions". In a separate task, three workers are asked to identify the actions performed in every sentence of the development and test set recipes. If an action receives a majority vote that it is performed, it is included in the annotations.