Proximal Policy Optimization and its Dynamic Version for Sequence Generation

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Abstract

In sequence generation task, many works use policy gradient for model optimization to tackle the intractable backpropagation issue when maximizing the non-differentiable evaluation metrics or fooling the discriminator in adversarial learning. In this paper, we replace policy gradient with proximal policy optimization (PPO), which is a proved more efficient reinforcement learning algorithm, and propose a dynamic approach for PPO (PPO-dynamic). We demonstrate the efficacy of PPO and PPOdynamic on conditional sequence generation tasks including synthetic experiment and chitchat chatbot. The results show that PPO and PPO-dynamic can beat policy gradient by stability and performance.

1 Introduction

The purpose of chit-chat chatbot is to respond like human when talking with people. Chit-chat has the one-to-many property, that is, given an input sentence, there are many possible answers. For example, when a user says "How is the weather?", the ideal responses include "Today's weather is good." and "It's raining.", etc.

The recent success of sequence-to-sequence model (Sutskever et al., 2014) as chatbot (Vinyals and Le, 2015) inspires researchers to study how to improve generative model based chatbot to beat the rule-based and retrieval-based chatbots by coherence, creativity and its main disadvantage: robustness. Many state-of-the-art algorithms are thus applied to this text generation task, such as generative adversarial networks (GANs) (Yu et al., 2017; Che et al., 2017; Gulrajani et al., 2017; Lin et al., 2017; Tuan and Lee, 2018) and reinforcement learning (Ranzato et al., 2015).

Particularly, the policy gradient based method REINFORCE (Ranzato et al., 2015) is used to op-

timize the BLEU score (Papineni et al., 2002) in text generation, and policy gradient with Monte-Carlo tree search (MCTS) is also used to optimize sequence generative adversarial network (SeqGAN) (Yu et al., 2017; Li et al., 2017). Despite of the reported good performance, policy gradient empirically leads to destructively updates and thus easily adopts similar actions. Moreover, policy gradient makes the training of SeqGAN more unstable than regular GANs. The recent proposed method, proximal policy optimization (PPO) (Schulman et al., 2017), can deal with the problems by regularizing the gradient of policy.

Because we have observed that the unstability of policy gradient in both reinforcement learning and GANs limits the performance, it is desired to replace policy gradient with the more efficient optimization method: PPO. In addition, we modify the constraints of PPO to make it both dynamic and more flexible, and show that this modification can further improve the training.

2 Related Works

Previous pure reinforcement learning based approaches attempt to fine-tune text generation model to optimize BLEU scores. These approaches include REINFORCE, MIXER (Ranzato et al., 2015), and actor-critic approach (Bahdanau et al., 2016). They are the very first attempts to apply reinforcement learning to seq2seq and show promising performance. Nonetheless, on Atari games and continuous control domains, many approaches are proposed to improve the scalability (Schulman et al., 2015), data efficiency (Popov et al., 2017), and robustness (Pinto et al., 2017). These techniques are not yet explored on text generation.

A recent well-known method for improving

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chit-chat chatbot is using adversarial learning (i.e., GANs) (Li et al., 2017; Che et al., 2017; Lin et al., 2017; Rajeswar et al., 2017; Press et al., 2017; Tuan and Lee, 2018). Because the discrete text makes the backpropagation through GANs intractable, researchers have proposed several approaches to deal with it. Among them, Gumbelsoftmax (Kusner and Hernández-Lobato, 2016) and policy gradient (Yu et al., 2017) are the most widely used.

Policy gradient has shown promising results but still left rooms for improvements. By intuition, policy optimization methods that have been proved much more efficient than policy gradient should be applied to the conditional text generation task.

3 Background

We use gated recurrent unit (GRU) to build a sequence-to-sequence model (seq2seq) as our chit-chat chatbot. The seq2seq model contains an encoder and a decoder that the encoder reads in an input sentence $\{x_t\}_{t=1}^{N}$ and the decoder predicts an output sentence $\{y_t\}_{t=1}^{M}$, where x_t and y_t are words, and N and M are the length of input and output respectively.

Sentence generation can be formulated as a Markov decision process (MDP) (S, A, T, R, γ) , where S is a set of states $s_t = \{x, y_{1:t-1}\}, A \text{ is a set of actions } a_t = y_t,$ T is the transition probability of the next state given the current state and action R is a reward function $r(s_t, a_t)$ for every intermediate time step t, and γ is a discount factor that $\gamma \in [0,1]$. The actions are taken from a probability distribution called policy π given the current state (i.e., $a_t \sim \pi(s_t)$). In sentence generation, π is a seg2seg model. Therefore, reinforcement learning methods are suitable to apply to sentence generative model by learning the seq2seq model, or policy π , that can gain as much as possible reward.

As previous works, we can use two types of reward functions: (1) task-specific scores (i.e., BLEU (Papineni et al., 2002)), (2) discriminator scores in GANs (Li et al., 2017).

3.1 Policy Gradient

Given reward r_t at each time step t, the parameter θ of policy π (a seq2seq model) is updated by policy gradient as following:

$$\nabla_{\theta} = A_t \nabla_{\theta} \pi_{\theta}(a_t, s_t), \tag{1}$$

where $A_t = \sum_{\tau=t}^M \gamma^{\tau-t} r_{\tau} - b$ is the 1-sample estimated advantage function, in which b is the baseline² to reduce the training variance³. A_t can be interpreted as the goodness of adopted action a_t over all the possible actions at state s_t . Policy gradient directly updates θ to increase the probability of a_t given s_t when advantage function is positive, and vise versa.

3.2 Proximal Policy Optimization

Proximal policy optimization (PPO) (Schulman et al., 2017) is modified from trust region policy optimization (TRPO) (Schulman et al., 2015), and both methods aim to maximize a surrogate objective and subject to a constraint on quantity of policy update:

$$\begin{split} \max_{\theta} & L^{TRPO}(\theta), L^{TRPO}(\theta) = \mathbb{E}[\frac{\pi_{\theta}(a_t|s_t)}{\pi_{\theta_{old}}(a_t|s_t)} A_t], \\ \text{subject to} \quad & \mathbb{E}[\text{KL}[\pi_{\theta_{old}}(a_t|s_t), \pi_{\theta}(a_t|s_t)]] \leq \delta. \end{split} \tag{2}$$

 θ_{old} is the old parameters before update. Because the KL-divergence between π_{θ} and $\pi_{\theta_{old}}$ is bounded by δ , the updated policy π_{θ} cannot be too far away from the old policy $\pi_{\theta_{old}}$.

PPO uses a clipped objective to heuristically constrain the KL-divergence:

$$\max_{\theta} L^{PPO}(\theta),$$

$$L^{PPO}(\theta) = \mathbb{E}[\min(\rho_t A_t, clip(\rho_t, 1 - \epsilon, 1 + \epsilon) A_t)]$$
(3)

where $\rho_t = \frac{\pi_{\theta}(a_t|s_t)}{\pi_{\theta_{old}}(a_t|s_t)}$ and ϵ is a hyperparameter (e.g., $\epsilon = 0.1$). When A_t is positive, the objective is clipped by $(1+\epsilon)$; when A_t is negative, the objective is clipped by $(1-\epsilon)$. L^{PPO} excludes the changes that will improve the objective, and

¹In sentence generation, transition probability is not needed because given the current state and action, the next state is determined, that is, $T(s_{t+1} = \{x, y_{1:t}\} | s_t = \{x, y_{1:t-1}\}, a_t = y_t) = 1$.

 $^{^2}$ The baseline b is often a value function that equals to the expected obtained rewards at the current state s_t .

 $^{^3}$ The term $\sum_{\tau=t}^{M} \gamma^{\tau-t} r_{\tau}$ is a 1-sample estimation of expected obtained rewards at current time step t after generating the whole sentence. It is the summation of the intermediate rewards from time t to the end, each is multiplied by a discount factor γ .

includes the changes that will make the objective worse⁴.

4 Proposed Approach

We propose to replace policy gradient on conditional text generation with PPO, which constraints the policy update by an assigned hyperparameter ϵ . Given the input sentence $\{x_t\}_{t=1}^N$, seq2seq predicts an output sentence $\{y_t\}_{t=1}^M$, where the words y_t are sampled from probability distribution $\pi_{\theta}(y_t|x,y_{1:t-1})$. By PPO, the update of seq2seq is to maximize L^{PPO} in Equation (3), where $\rho_t =$

 $\frac{\pi_{\theta}(y_t|x,y_{1:t-1})}{\pi_{\theta_{old}}(y_t|x,y_{1:t-1})}.$ In theory, the fixed hyperparameter ϵ that aims to bound the KL-divergence is not consistent with that KL-divergence is actually depending on the old policy π_{old} . Instead, we propose dynamic parameters that automatically adjust the bound to have better constraints, and call it PPO-dynamic in Section 5. The optimization is thus modified as below:

$$\nabla_{\theta} = \nabla_{\theta} \min(\rho_{t} A_{t}, clip(\rho_{t}, 1 - \beta, 1 + \alpha) A_{t})$$
where $\beta = \min(\beta_{1}, \beta_{2} \sqrt{1/\pi_{\theta_{old}} - 1})$

$$\alpha = \min(\alpha_{1}, \alpha_{2} \sqrt{1/\pi_{\theta_{old}} - 1})$$
(4)

where β_1 , β_2 , α_1 and α_2 are hyperparameters, and the derivation of the term $\sqrt{1/\pi_{\theta_{old}}-1}$ is written in the Supplementary Material. In most cases, it is sufficient to use $\alpha_1 = \beta_1 = \inf$ and $\alpha_2 = \beta_2$, so only one hyperparameter is left to tune. This setup is thus comparable to the original PPO.

We can interpret PPO-dynamic by that it gives bigger gradient tolerances for actions that have lower probability (i.e., $\pi_{\theta_{old}}(y_t|x, y_{1:t-1})$ is small), and vise versa. This mechanism then dynamically looses and tightens ϵ of PPO throughout the training.

5 **Experiments**

To validate the efficacy of using PPO and our proposed PPO-dynamic, we compare them with REINFORCE, MIXER, and SegGAN with policy gradient.

5.1 Synthetic Experiment: Counting

Counting (Tuan and Lee, 2018) is a one-to-many conditional sequence generation task that aims to

Algorithms		precision
MLE		87.01
REINFORCE		98.61
PPO		98.42
PPO-dynamic		98.62
MIXER	original	98.43
	PPO	98.39
	PPO-dynamic	98.42
SeqGAN	original	87.37
	PPO	87.24
	PPO-dynamic	91.85

Table 1: Results of different algorithms on counting task.

count the length and position of input sequence. Each input sequence can be represented as $\{x_t\}_1^N$, where x_t are digits 0-9 and N is ranging from 1 to 10; each output sequence is a three digits sequence that can be represented as $\{y_t\}_1^M$, where y_t are digits 0-9 and M must be 3. The output sequence must obey the rule that $y_2 = x_t$, where t is randomly selected from $\{1...N\}$, and $y_1 = t - 1$ and $y_3 = N - t$. For example, given an input sequence $\{9, 2, 3\}$, the possible output sequences contains $\{0, 9, 2\}, \{1, 2, 1\}$ and $\{2, 3, 0\}$

Because it is easy to judge if a generated sequence is correct or not, we can directly optimize the correctness, and estimate the precision, which is the number of correct answers divided by the number of all generated answers.

5.1.1 Results

In Table 1 and Figure 1, we compares the precision and learning curves of different algorithms on the counting task. As shown in Table 1, we observed a tremendous improvement in precision of SeqGAN by using PPO-dynamic instead of policy gradient, and PPO-dynamic can also achieve comparable performance (which is a very high precision) with REINFORCE and MIXER. The learning curves are plotted in Figure 1. We find out that the training progress of PPO is slower than PPOdynamic, which validates that dynamic constraints can facilitate the training.

To demonstrate the ability of giving diverse answers, we show the distribution of y_1 , a number related to input sentence length N, given a fixed N. Figure 2 shows the y_1 distribution of three policy optimization methods and the ground truth

⁴When A_t is positive, the objective is clipped by $(1 + \epsilon)$; when A_t is negative, the objective is clipped by $(1 - \epsilon)$.

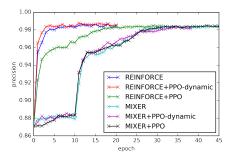


Figure 1: Learning curve of different algorithms on synthetic counting task.

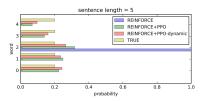


Figure 2: The average distribution of the first output y_1 when the input sentence length N equals to 5. The possible outputs are ranging from 0 to 4. The yellow bar shows the ground truth probability of each word.

distribution when fixing $N=5^5$. We can see that using REINFORCE will severely make the probability distribution concentrate on one word. On the other hand, the distribution given by PPO and PPO-dynamic are much closer to the ground truth distribution.

5.2 Chit-chat Chatbot: OpenSubtitles

For training chit-chat chatbot, we tested our algorithms on OpenSubtitles dataset (Tiedemann, 2009) and used BLEU-2 (Papineni et al., 2002; Liu et al., 2016)⁶ as the reward for reinforcement learning. Specifically, we organized both our training and testing data, and made them become that each input sentence has one to many answers. This made the evaluation of BLEU-2 score more correct by having multiple references.

5.2.1 Results

The BLEU-2 scores and learning curves of different optimization algorithms are presented in Table 2 and Figure 3. From the testing results in

Algorithms	BLEU
MLE	9.62
REINFORCE	14.29
PPO	14.12
PPO-dynamic	14.73

Table 2: The BLEU-2 Results of different algorithms on OpenSubtitles.

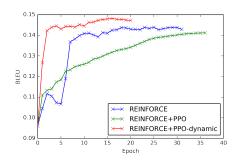


Figure 3: Learning curve of BLEU-2 for different algorithms on OpenSubtitles.

Table 2, we can see that the three optimization methods have comparable performance, but PPO-dynamic achieves a slightly higher BLEU-2 score than REINFORCE and PPO. Moreover, we find out that the training progress of both PPO and PPO-dynamic are more stable than policy gradient, and the training progress of PPO-dynamic is much faster than the others. This shows that PPO based methods can improve the high variance problem of using REINFORCE, and the dynamic constraint can help the learning converge quickly.

We demonstrate some responses of candidate model in Supplementary Material.

6 Conclusion

In this paper, we replace policy gradient with PPO on conditional sequence generation, and propose a dynamic approach for PPO to further improve the optimization process. By experiments on synthetic task and chit-chat chatbot, we demonstrate that both PPO and PPO-dynamic can stabilize the training and lead the model to learn to generate more diverse outputs. In addition, PPO-dynamic can speed up the convergence. The results suggest that PPO is a better way for sequence learning, and GAN-based sequence learning can use PPO as the new optimization method for better performance.

⁵For other sentence lengths, please refer to Supplementary Material.

⁶Previous work (Liu et al., 2016) suggests to use BLEU-2, which is proved to be more consistent with human score than BLEU-3 and BLEU-4.

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Proximal Policy Optimization and its Dynamic Version for Sequence Generation - Supplementary Material

Abstract

This supplementary material contains the derivation of our proposed PPO-dynamic, the experimental settings and more results.

A Derivation of the Constraints of PPO-dynamic

Because we want to find real constraints for PPO, we define that $\frac{P(a)}{P_{old}(a)}=1+\alpha(a)$, and aim to find $\alpha(a)$ so that $KL(P_{old}||P)\leq\delta$. First,

$$KL(P_{old}||P) = -\int_{x} P_{old}(x) \ln \frac{P(x)}{P_{old}(x)} dx$$

$$= -P_{old}(a) \ln \frac{P(a)}{P_{old}(a)} + \int_{x \neq a} P_{old}(x) \ln \frac{P_{old}(x)}{P(x)} dx$$

$$= -P_{old}(a) \ln(1 + \alpha(a)) + \int_{x \neq a} P_{old}(x) \ln \beta(x) dx$$
(1)

where $\beta(x)$ is defined as $\beta(x) = \frac{P_{old}(x)}{P(x)}$.

By assuming $\beta(x)$ is a constant β for all $x \neq a$, we can find the value of β by following:

$$1 = \int_{x \neq a} P(x)dx + P(a)$$

$$= \frac{1}{\beta} \int_{x \neq a} P_{old}(x)dx + (1 + \alpha(a))P_{old}(a) \quad (2)$$

$$= \frac{1}{\beta} (1 - P_{old}(a)) + (1 + \alpha(a))P_{old}(a)$$

so.

$$\beta = \frac{1 - P_{old}(a)}{1 - (1 + \alpha(a))P_{old}(a)}$$
(3)

After substituting the term $\beta(x)$ in Equation (1) by Equation (3), we can get:

$$KL(P_{old}||P) = -P_{old}(a) \ln(1 + \alpha(a))$$

$$+ (1 - P_{old}(a)) \ln\left(\frac{1 - P_{old}(a)}{1 - (1 + \alpha(a))P_{old}(a)}\right)$$

$$= -P_{old}(a) \ln(1 + \alpha(a))$$

$$- (1 - P_{old}(a)) \ln\left(1 - \alpha(a)\frac{P_{old}(a)}{1 - P_{old}(a)}\right)$$
(4)

Now we assume that $\alpha(a) \ll 1$, and then we can use Taylor expansion for $\ln(1 + \alpha(a))$ and $\ln(1 - \alpha(a) \frac{P_{old}(a)}{1 - P_{old}(a)})$ such that:

$$\ln(1 + \alpha(a)) \doteq \alpha(a) - \frac{\alpha(a)^{2}}{2},
\ln(1 - \alpha(a) \frac{P_{old}(a)}{1 - P_{old}(a)})
\doteq -\alpha(a) \frac{P_{old}(a)}{1 - P_{old}(a)} - \frac{\alpha(a)^{2}}{2} \frac{P_{old}(a)^{2}}{(1 - P_{old}(a))^{2}}$$
(5)

By substituting the terms in Equation (4), we have:

$$KL(P_{old}||P) \doteq -P_{old}(a)(\alpha(a) - \frac{\alpha(a)^{2}}{2})$$

$$+ (1 - P_{old}(a)) \left(-\alpha(a) \frac{P_{old}(a)}{1 - P_{old}(a)} - \frac{\alpha(a)^{2}}{2} \frac{P_{old}(a)^{2}}{(1 - P_{old}(a))^{2}} \right)$$

$$= \frac{P_{old}(a)}{1 - P_{old}(a)} \frac{\alpha(a)^{2}}{2} \leq \delta$$
(6)

so we get.

$$-\sqrt{2\delta}\sqrt{\frac{1-P_{old}(a)}{P_{old}(a)}} \le \alpha(a) \le \sqrt{2\delta}\sqrt{\frac{1-P_{old}(a)}{P_{old}(a)}}$$
(7)

that is, when we want to constrain PPO by restricting $\frac{P(a)}{P_{old}(a)}$, we have to constrain $\alpha(a)$ by $\sqrt{\frac{1-P_{old}(a)}{P_{old}(a)}}$, or $\sqrt{\frac{1}{P_{old}(a)}-1}$.

B Pseudo Code of PPO and PPO-dynamic

The pseudo code is listed in Algorithm 1 and is basically the same as PPO algorithm (Schulman et al., 2017).

C Experimental Setup

The baseline in advantage function A_t is trained as (Ranzato et al., 2015). The best hyperparameters we found out by grid search is that, for RE-INFORCE and MIXER with PPO-dynamic, α_1 =

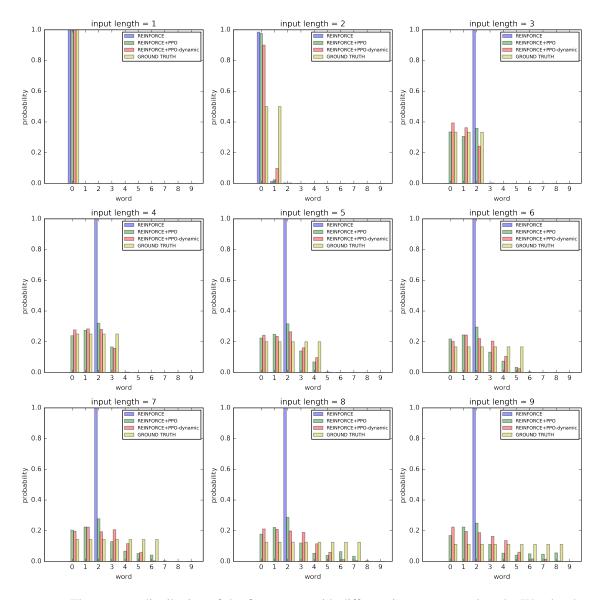


Figure 1: The average distribution of the first output with different input sentence length. We plot the probability from 0 to 9. The yellow box is the ground truth probability of each word. The blue box and the red box shows the probability of each word trained by REINFORCE and REINFORCE with dynamic PPO.

 $\beta_1 = +inf$ and $\alpha_2 = \beta_2 = 1.0$; for SeqGAN with PPO-dynamic, $\alpha_1 = 10.0$, $\beta_1 = 0.5$, and $\alpha_2 = \beta_2 = 0.2$; for REINFORCE, MIXER and SeqGAN with original PPO, $\epsilon = 0.2$.

We use 1 layer GRU with 128 dimension for Counting task, and 1 layer GRU with 512 dimension for chit-chat chatbot.

D Distribution of the first output with different input sentence length

We want to check the distribution of the first output on counting task in order to get an intuitive impression of the ability to response different answers, so we plot the distribution of all the input length in Figure 1. We can see that using REIN-FORCE method will make the distribution tremendously concentrate on word 2 when the input sentence length is bigger than 2. On the other hand, using PPO method will generate a more scattered

Algorithm 1 PPO and PPO-dynamic

```
Initialize \pi
Pretrain \pi using MLE and set \pi_{old} = \pi
Initialize discriminator D, value network V
for number of training iterations do
sample a batch of data \{y_t\}_{t=1}^M using \pi_{old} set \pi_{old} = \pi
optimize \pi using L^{PPO} and the sampled data \{y_t\}_{t=1}^M
end for
```

Length	REINFORCE	PPO-dynamic
1	0.066	0.090
2	0.064	0.076
3	0.066	0.029
4	0.066	0.018
5	0.066	0.014
6	0.066	0.012
7	0.066	0.011
8	0.066	0.011
9	0.066	0.010

Table 1: The mean variance of the distribution of the first generated word. Length means the input sentence length, and we average all the variance of the distribution.

distribution and is much closer to the ground-truth distribution.

We also evaluate the variance of output distribution. The higher the variance, the sharper the distribution. Therefore, it is intuitive to claim that a shorter length input should correspond to a higher variance, and vise versa. We can clearly see the claim in Table 1. REINFORCE always generate a sharp distribution; PPO-dynamic can adjust the distribution according to the input.

E Some output example

In Table 2, we present some examples of our trained chit-chat chatbot by optimizing BLEU-2 scores using REINFORCE, PPO and PPO-dynamic.

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Alec Radford, and Oleg Klimov. 2017. Proximal policy optimization algorithms. *arXiv preprint arXiv:1707.06347*.

input	what can i do for you.
MLE	i 'm gonna go back .
REINFORCE	go!
PPO	i don 't know what i 'm talking about .
PPO-dynamic	i don 't know .
input	go, go, go!
MLE	go, go, go, go, go!
REINFORCE	go!
PPO	go on the way.
PPO-dynamic	go! go get him go!
input	i said
MLE	i 'm sorry .
REINFORCE	i 'm not .
PPO	i 'm sorry .
PPO-dynamic	oh , i 'm sorry .
input	it 's wonderful .
MLE	i 'm not gonna be there .
REINFORCE	it 's you .
PPO	it 's a good idea.
PPO-dynamic	it 's a good idea.
input	i don 't know what you 're talking about .
MLE	you 're gonna be a man .
REINFORCE	i 'm not .
PPO	you 're not gonna be a good man who 's not really you think.
PPO-dynamic	you 're gonna be a good man , you know .
input	come here
MLE	i 'll be back in the morning.
REINFORCE	come here.
PPO	i 'm not you 're a little girl .
PPO-dynamic	you 're not my father.
input	get him down .
MLE	get him out of here!
REINFORCE	get him
PPO	get him out of it.
PPO-dynamic	get him out of there .
input	change your mind.
MLE	i 'll be back in the morning.
REINFORCE	i 'll not .
PPO	i 'm not you sure i can 't do it.
PPO-dynamic	i 'm not my father.
input	let him go .
MLE	he 's gonna be there.
REINFORCE	he 's a little girl .
PPO	he 's a little girl .
PPO-dynamic	go on the phone.

Table 2: Results of different algorithms on real task.