

機械学習を用いた 機能分子の自動設計

津田宏治

東京大学/物材機構/理研AIP

Deep Learning: 予測から生成へ

Art

Can Google's Deep Dream become an art machine?

The company's neural network has created a slew of beautiful and at times terrifying images, and is being harnessed to create unique artwork



1754 207

Alex Rayner

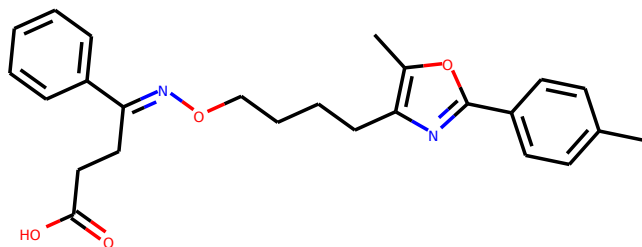
Monday 28 March 2016
22.51 BST



 Moonage Daydream: art created by Deep Dream. Photograph: Deep Dream

新規化合物生成

機械学習(予測)



Properties:

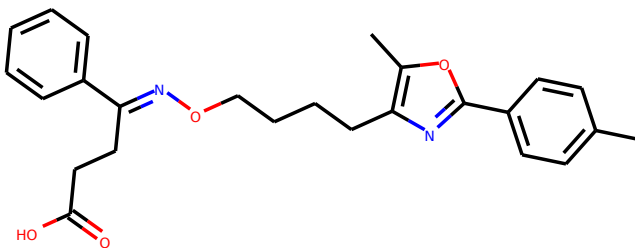
Binding Score
Bio Activity
ADMET

...

望ましい性質&
正しい(存在可能な)化合物の生成

SMILES

- SMILESの例



Cc3ccc(c2nc(CCCCO/N=C(CCC(O)=O)c1ccccc1)c(C)o2)cc3

- SMILESの要素

Atom: {C, c, o, O, N, F, [C@@H], n, -, S, Cl, [O-], [C@H], [NH+], [C@], s, Br, [nH], [NH3+], [NH2+], [C@@], [N+], [nH+], [S@], [N-], [n+], [S@@], [S-], I, [n-], P, [OH+], [NH-], [P@@H], [P@@], [PH2], [P@], [P+], [S+], [o+], [CH2-], [CH-], [SH+], [O+], [s+], [PH+], [PH], [S@@+]}

Bonds: {/, =, ¥# }

Ring: {1, 2, 3, 4, 5, 6, 7, 8, 9}

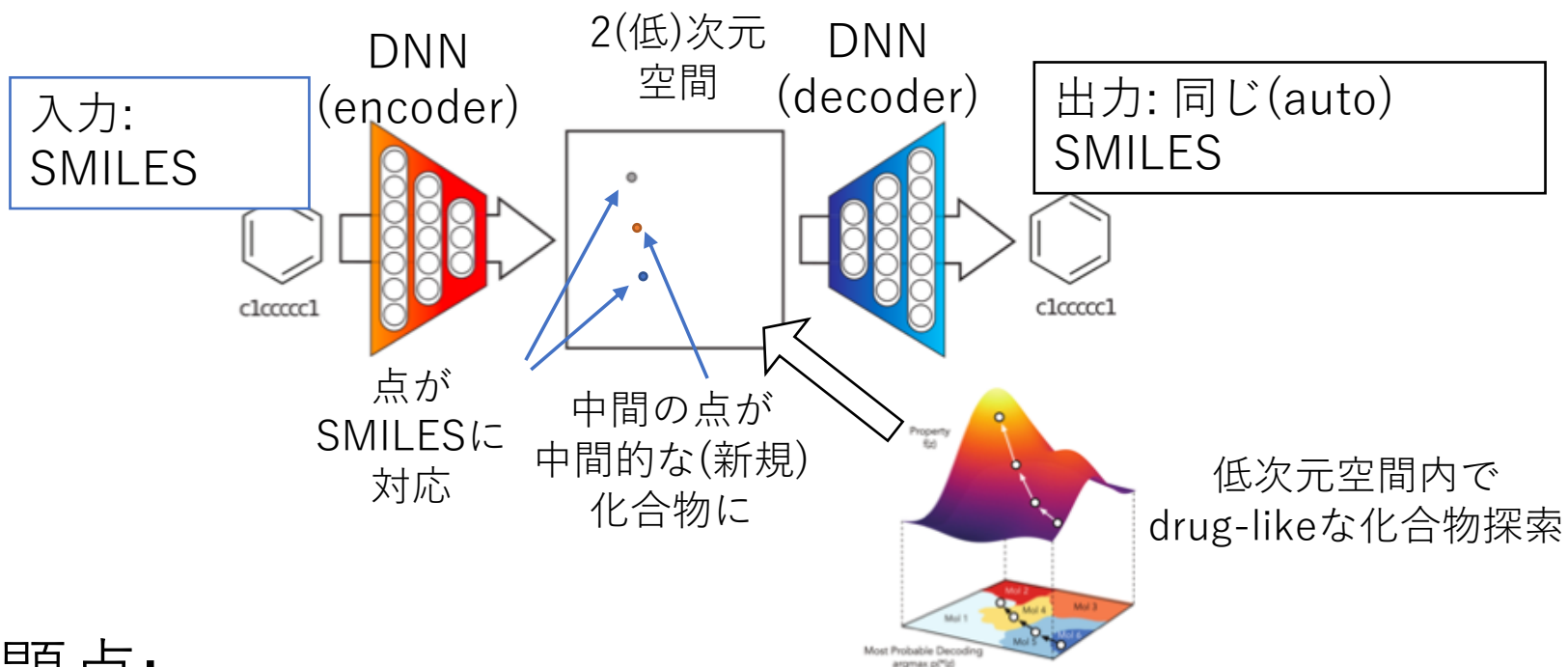
Branch: {(,)}

De novo 化合物生成

- これまでの化合物自動生成法は、あらかじめ定義されたFragmentを組み合わせるものが多かった
- 深層学習によるde novo生成
 - Variational autoencoder (Kusner et al., ICML 2017)
 - Recurrent neural network (Segler et al., Arxiv, 2017)
- ChemTS (<https://github.com/tsudalab/ChemTS>)
 - モンテカルロ木探索 + Recurrent Neural Network

VAEに基づく化合物生成

- Variational Auto Encoder (VAE).



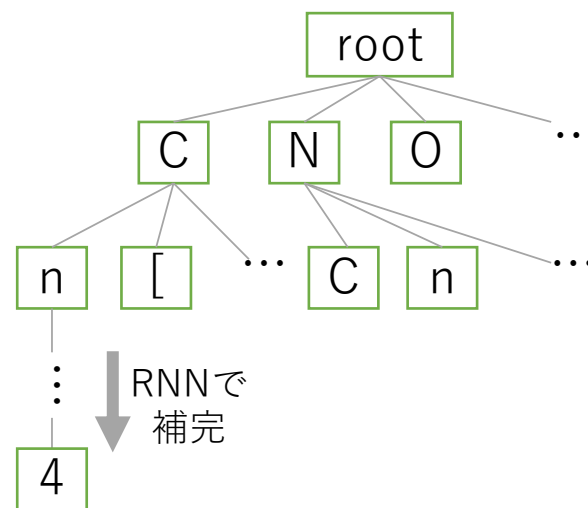
- 問題点:

- 正しい SMILES の生成確率が低い (0.4% → 5% 程度)
- 遅い

Gómez-Bombarelli et al., "Automatic chemical design using a data-driven continuous representation of molecules," Arxiv, 2016.
Kusner et al., "Grammar Variational Autoencoder," ICML, 2017.

ChemTS: MCTS and RNN

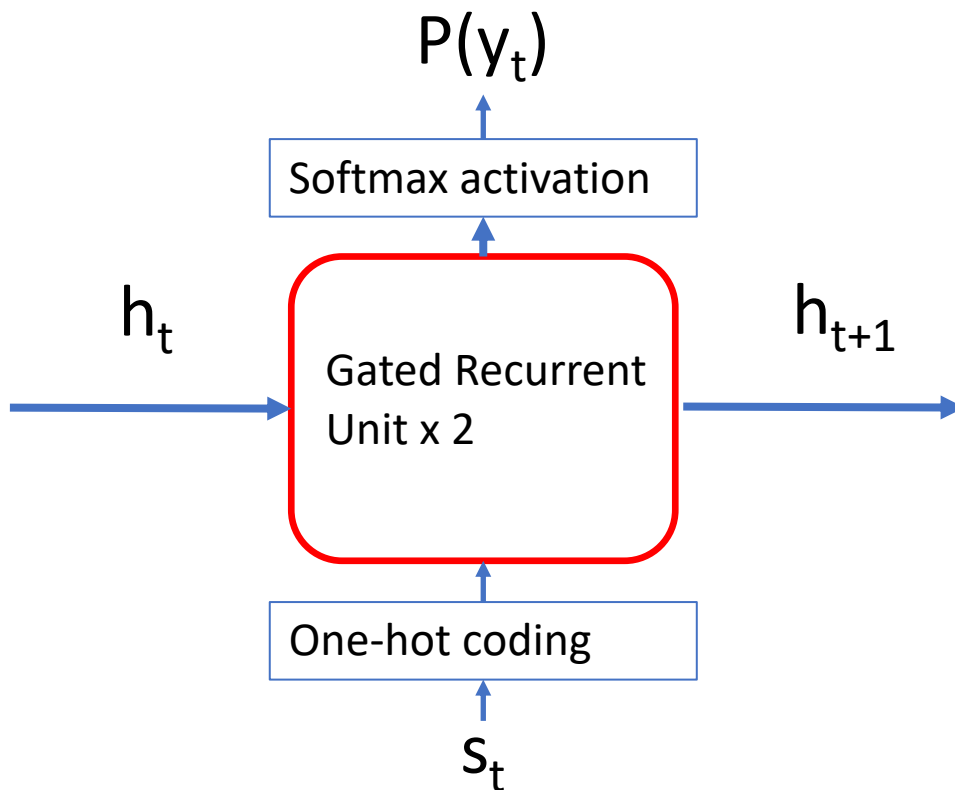
- SMILES文字列の探索木
- 最初はRootのみ
- MCTSを用いて探索木を徐々に伸ばす
- 中間ノードは、SMILESのprefixに対応
- RNNを用いて完全なSMILESに補完する



有効なSMILES生成の確率が高い(40%超)
高速な生成が可能

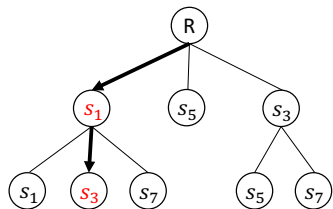
RNN : 25万化合物で訓練

- 入力 : 文字列 s_1, \dots, s_T
- 出力 : 文字列の確率分布 $P(y_1), \dots, P(y_T)$
- 出力は、入力を右に一文字シフトしたもの



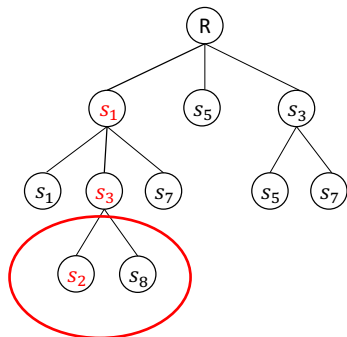
MCTSによる探索

(a) Selection

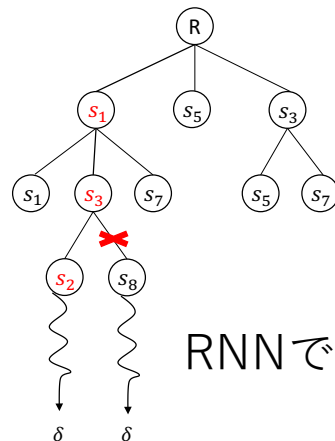


各ノードのスコア

(b) Expansion

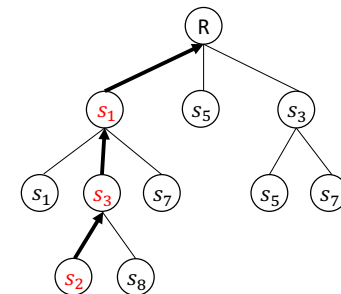


(c) Simulation



RNNで補完

(d) Backpropagation



全体のスコアを更新

$$u_i = \frac{w_i}{v_i} + C \frac{\sqrt{2 \ln V_{parent}}}{v_i}$$

子ノードのスコアの平均

“伸びしろ”

有効なSMILESのみ以下の drug-likenessの値を評価

$$J(m) = \log P(m) - SA(m) - RingPenalty(m)$$

(Gómez-Bombarelli et al. ICML2016)

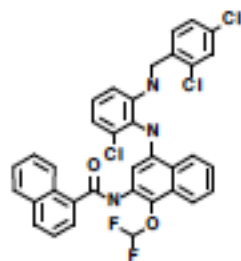
$$w_i = w_i + r$$

$$v_i = v_i + 1$$

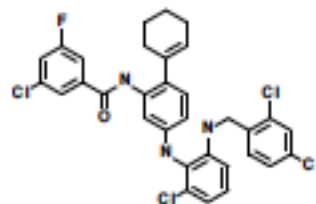
Table 1. Maximum score J at time points 2,4,6 and 8 hours achieved by different molecular generation methods. The rightmost column shows the number of generated molecules per minute. The average values and standard deviations over 10 trials are shown.

Method	2h	4h	6h	8h	Molecules/Min
ChemTS	4.91 ± 0.38	5.41 ± 0.51	5.49 ± 0.44	5.58 ± 0.50	40.89 ± 1.57
RNN+BO	3.54 ± 0.27	4.46 ± 0.24	4.46 ± 0.24	4.46 ± 0.24	8.33 ± 0.00
Only RNN	4.51 ± 0.27	4.62 ± 0.26	4.79 ± 0.25	4.79 ± 0.25	41.33 ± 1.42
CVAE+BO	-30.18 ± 26.91	-1.39 ± 2.24	-0.61 ± 1.08	-0.006 ± 0.92	0.14 ± 0.08
GVAE+BO	-4.34 ± 3.14	-1.29 ± 1.67	-0.17 ± 0.96	0.25 ± 1.31	1.38 ± 0.91

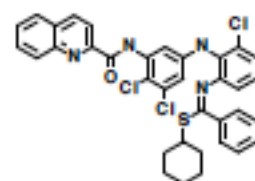
SMILES representation	<i>J</i>
<chem>O=C(Nc1cc(Nc2c(Cl)cccc2NCc2ccc(Cl)cc2Cl)c2ccccc2c1OC(F)F)c1cccc2ccccc12</chem>	6.56
<chem>O=C(Nc1cc(Nc2c(Cl)cccc2NCc2ccc(Cl)cc2Cl)ccc1C1=CCCC1)c1cc(F)cc(Cl)c1</chem>	6.43
<chem>O=C(Nc1cc(Nc2c(Cl)cccc2N=C(SC2CCCC2)c2ccccc2)cc(Cl)c1Cl)c1ccc2ccccc2n1</chem>	6.34
<chem>O=C(Nc1cc(Oc2ccc(Cl)cc2Cl)ccc1Nc1cc(Cl)ccc1Cl)c1ccc(Cl)cc1</chem>	6.33
<chem>O=C(Nc1cc(Nc2c(Cl)cccc2Cl)c(Cl)cc1Br)N(c1ccccc1)c1ccc(Cl)cc1</chem>	6.26
<chem>O=C(Nc1cc(Oc2c(Cl)cccc2Oc2ccc(-c3ccccc3)cc2)ccc1Cl)c1ccccc1</chem>	6.19
<chem>O=C(Nc1cc(Nc2c(Cl)cccc2Cl)c(Cl)c(C(=O)N(Cc2ccccc2)c2ccccc2)c1Cl)c1ccccc1F</chem>	6.08
<chem>O=C(Nc1cc(Oc2ccc(Cl)cc2Cl)cc(Cl)c1Cl)c1ncoc1-c1ccc(Sc2ccccc2)cc1</chem>	6.007
<chem>O=C(Nc1cc(Nc2c(Cl)cccc2NCc2ccc(Cl)cc2Cl)c2nccccc2c1Cl)c1ccc(Cl)cc1</chem>	6.0067
<chem>O=C(Nc1cc(Nc2c(Cl)cccc2NCc2ccc(Cl)cc2)c(Cl)cc1Cl)c1cc(F)ccc1Cl</chem>	6.0062



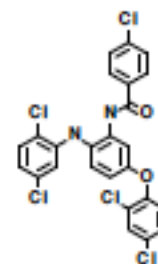
J = 6.56



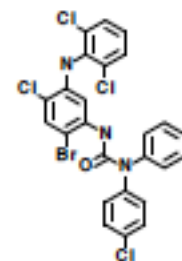
J = 6.43



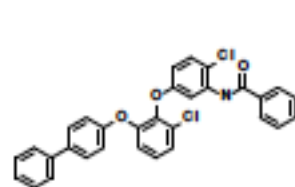
J = 6.34



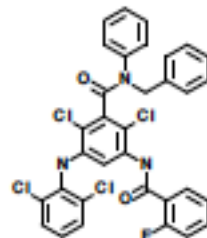
J = 6.33



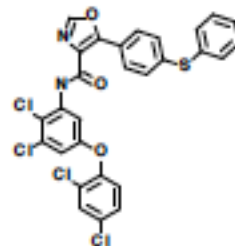
J = 6.26



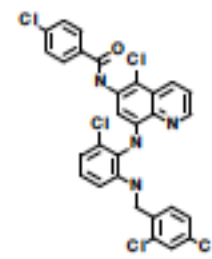
J = 6.19



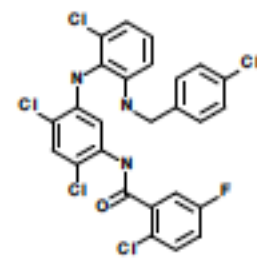
J = 6.08



J = 6.007



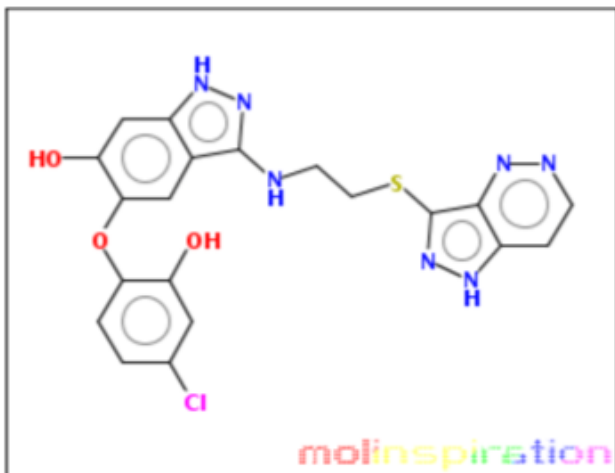
J = 6.0067



J = 6.0062

Docking to CDK2 (ChemTS + rDock)

originalSMILES Oc1cc(Cl)ccc1Oc1cc2c(NCCSc3n[nH]c4ccnnc34)n[nH]c2cc1O
miSMILES: Oc1cc(Cl)ccc1Oc1cc2c(NCCSc3n[nH]c4ccnnc34)n[nH]c2cc1O



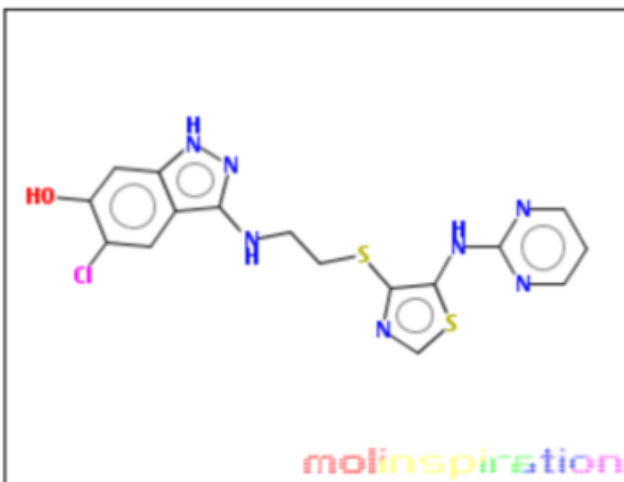
[Molinspiration bioactivity score](#) v2016.03

GPCR ligand	0.29
Ion channel modulator	0.13
Kinase inhibitor	0.64
Nuclear receptor ligand	-0.15
Protease inhibitor	0.05
Enzyme inhibitor	0.15

[Get data as text](#) (for copy / paste).

[Get 3D geometry](#) BETA

originalSMILES Oc1cc2[nH]nc(NCCSc3ncsc3Nc3ncccn3)c2cc1Cl
miSMILES: Oc1cc2[nH]nc(NCCSc3ncsc3Nc3ncccn3)c2cc1Cl



[Molinspiration bioactivity score](#) v2016.03

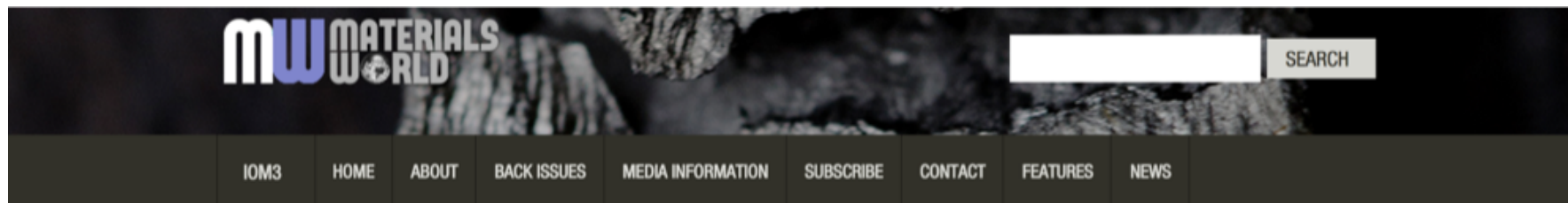
GPCR ligand	0.20
Ion channel modulator	-0.01
Kinase inhibitor	0.93
Nuclear receptor ligand	-0.43
Protease inhibitor	0.13
Enzyme inhibitor	0.19

[Get data as text](#) (for copy / paste).

[Get 3D geometry](#) BETA

おわりに

- Clever but slow (BO) 対 Stupid but fast (MCTS)
- **Wanted:** 合成ルート自動生成



■ GAME CHANGER

Ellis Davies

Materials World magazine, 1 Oct 2017

Ellis Davies reports on a method for designing advanced materials using an algorithm created to beat computer games.

An algorithm that identifies the best moves to beat computer games – the Monte Carlo tree search (MCTS) – has been used to develop a tool that allows researchers to determine the ideal placements for atoms within a structure to design advanced materials, such as metal and polymer matrix materials.



Monte Carlo tree search (MCTS) for a binary atom assignment problem. The

2017
2016
2015
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