脳のコンポーネント図の作り方：
プロセス間関係の整理と確率モデルによる記述

WBA LECTURE
The Whole Brain Architecture Initiative,

第2部 確率モデルによる脳のコンポーネント図の作り方

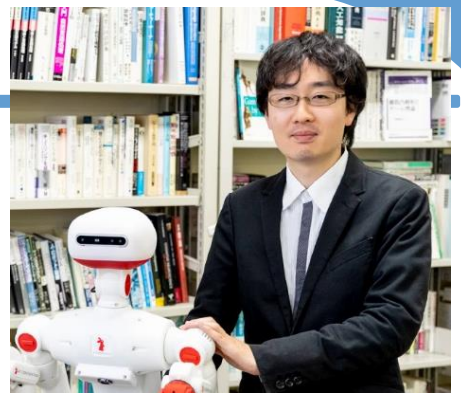
確率的生成モデルへの変換方法と実例紹介

立命館大学
情報理工学部
講師　谷口 彰

RITSUMEIKAN

Emergent System Lab.

自己紹介



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所属： 立命館大学 情報理工学部 創発システム研究室

略歴

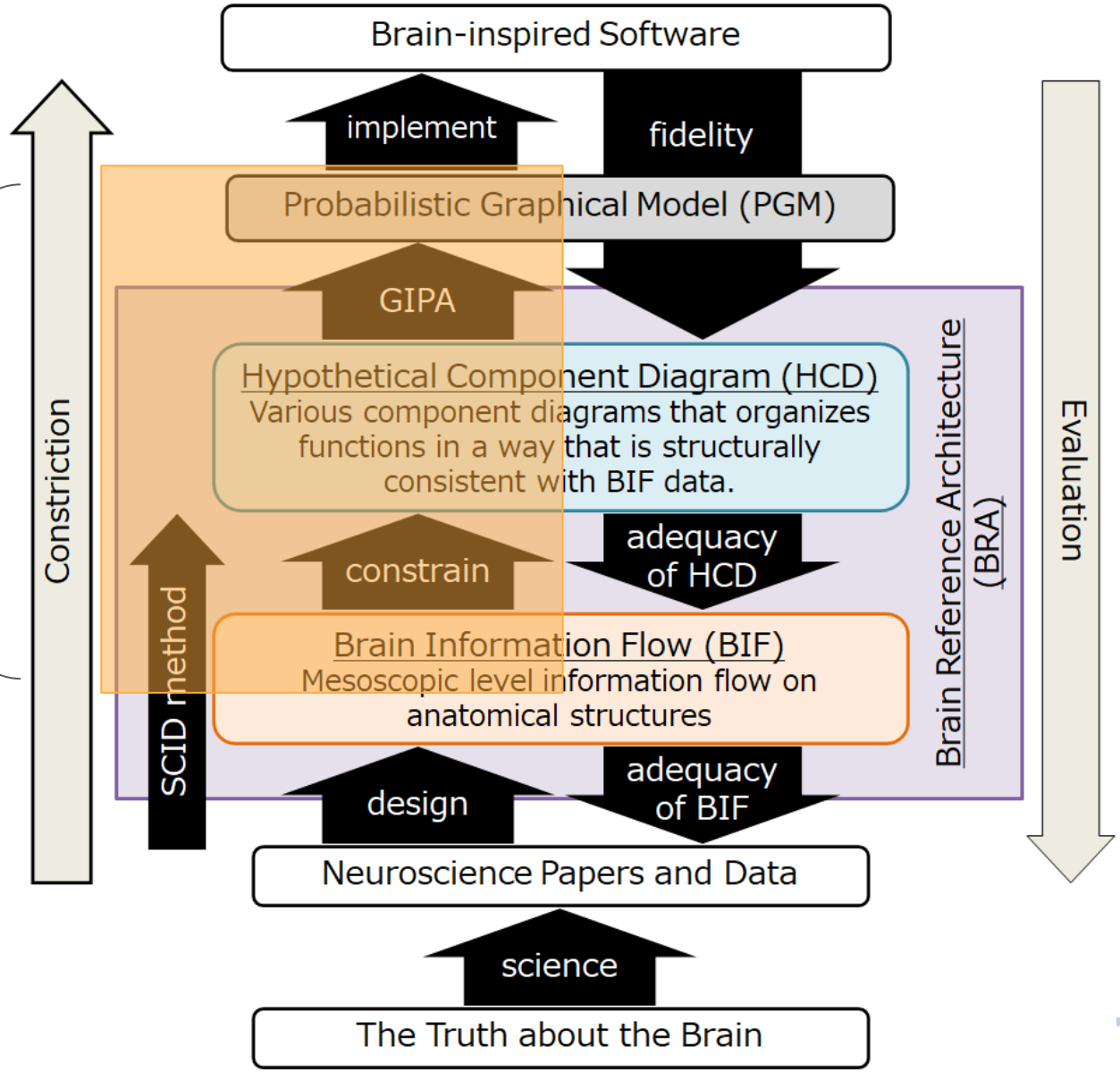
- ◆ 2013年 3月　立命館大学 情報理工学部 知能情報学科　卒業　学士（工学）
- ◆ 2015年 3月　立命館大学大学院 情報理工学研究科 博士前期課程　修了　修士（工学）
- ◆ 2018年 3月　立命館大学大学院 情報理工学研究科 博士後期課程　修了　博士（工学）
- ◆ 2015年 5月～2017年 3月　立命館大学　総合科学技術研究機構　リサーチアシスタント
- ◆ 2016年 4月～2016年 7月　Visiting research student, Centre for Robotics and Neural Systems Research Group, Plymouth University, U.K.
- ◆ 2017年 4月～2019年 3月　日本学術振興会 特別研究員 (DC2, PD)
- ◆ 2019年 4月～2022年 3月　立命館大学 情報理工学部 特任助教
- ◆ 2022年 4月～　立命館大学 情報理工学部 講師

主な研究テーマ：「確率的生成モデルに基づくロボットによる場所概念および語彙の獲得」

- ➢ 位置情報・言語情報・画像情報といったマルチモーダル情報から，教師なし機械学習手法により場所概念（場所のカテゴリ）や場所に関する語彙の獲得を目指す研究.
- ➢ 記号創発ロボティクス・機械学習・知能ロボット

本レクチャーの全体構成

足場の上にPGMを構築する(谷口)
- PGM作成(GIPA)
- HCD作成



目次

1. これまでの取り組み紹介
2. BRAとしての確率的生成モデル（PGM）構築：GIPA
3. **HF-PGM：海馬体を参照した確率的生成モデル**
    1. 海馬体の脳科学的知見
    2. HF-PGMのグラフィカルモデル
4. **音声言語の二重分節解析を担う確率的生成モデル**
    1. 聴覚野・言語野の脳科学的知見
    2. DAA-PGMのグラフィカルモデル
5. まとめ

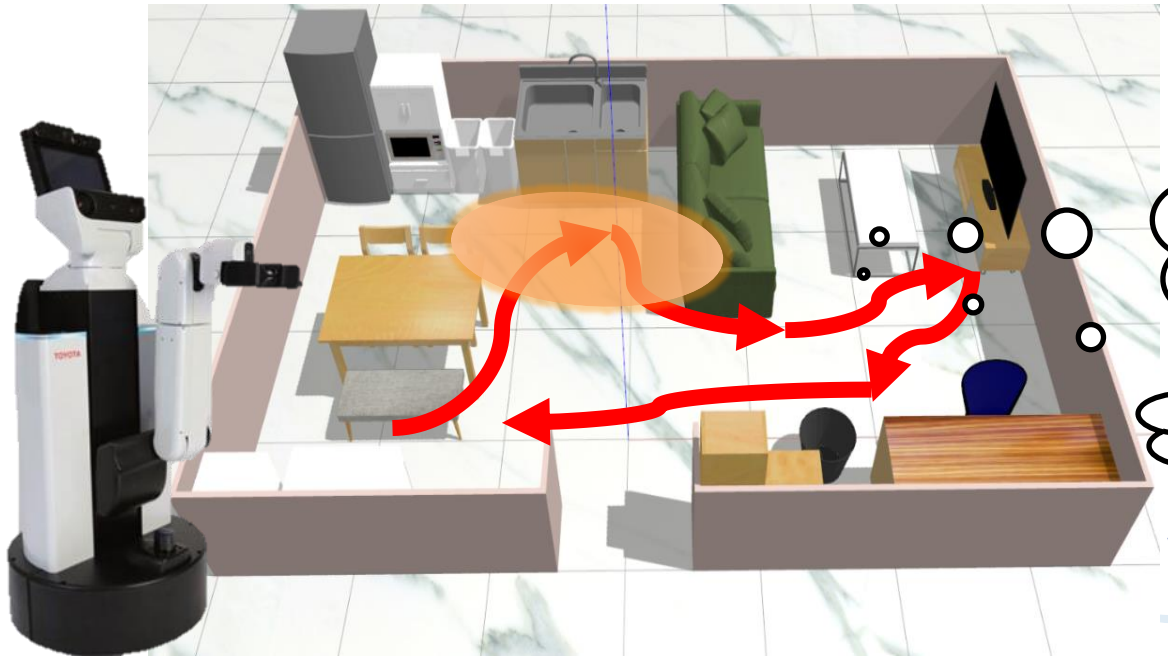
今回の発表の論文URL：

- Hippocampal formation-inspired probabilistic generative model
    - https://www.sciencedirect.com/science/article/pii/S0893608022001332
- Brain-inspired probabilistic generative model for double articulation analysis of spoken language
    - https://arxiv.org/abs/2207.02457

BRAアプローチ以外の
これまでの取り組み

これまでの取り組み：研究背景

- 人間の様々な生活環境で動作するロボットは，未知環境において適応的に**場所概念（場所のカテゴリ知識）や語彙**を学習することが求められる．
  - 対象の範囲が明確ではなく，環境や人によって異なる場所概念を事前に人手で設計することは難しい．
  - ロボットが**自らの経験を元に自律的に概念を形成**する必要がある．



音声言語（場所の名前）

“きっちん”
“だいどころ”
“おかって”

このあたり？

視覚情報
（場所の画像特徴）

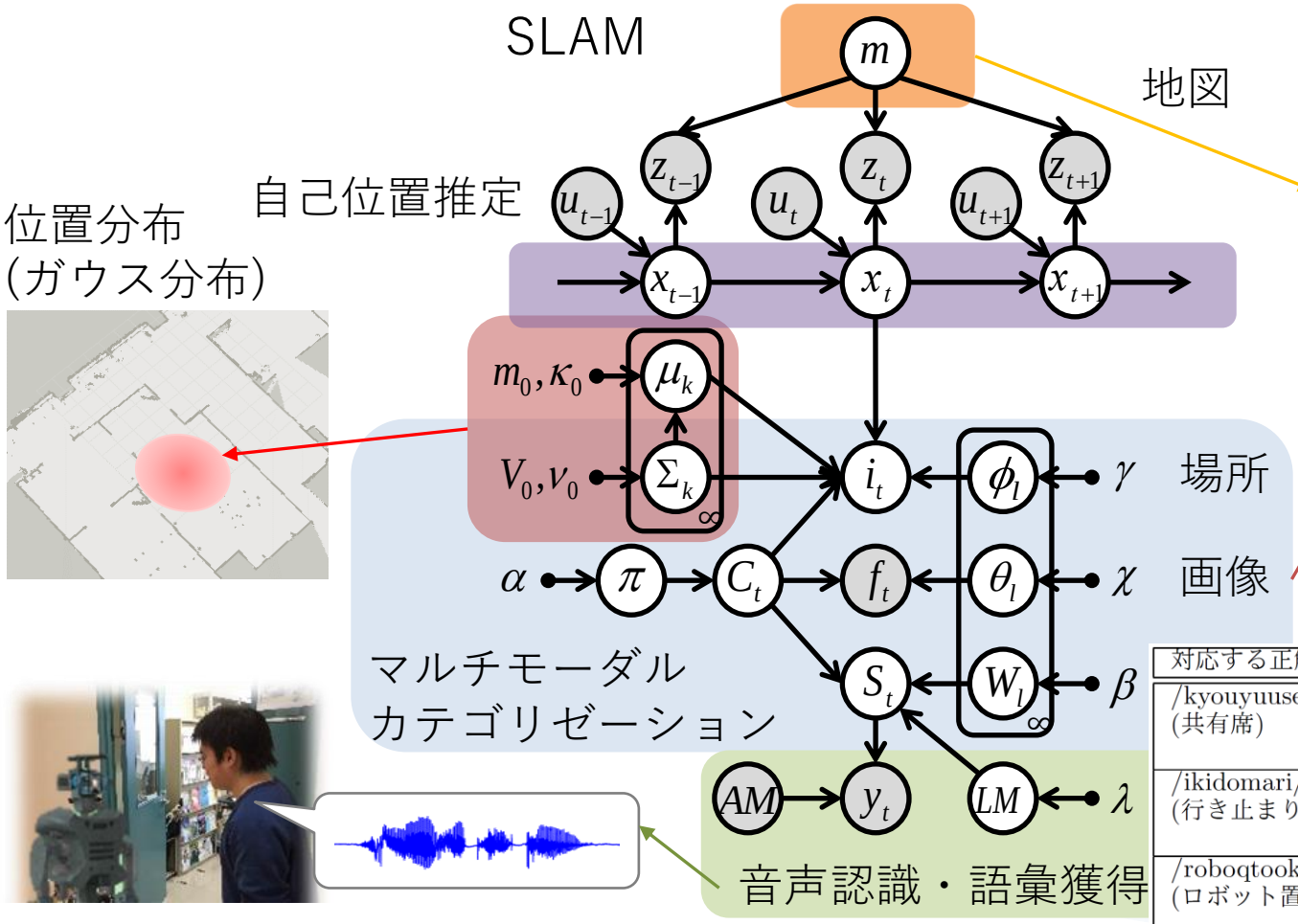
位置分布（空間的な広がり）

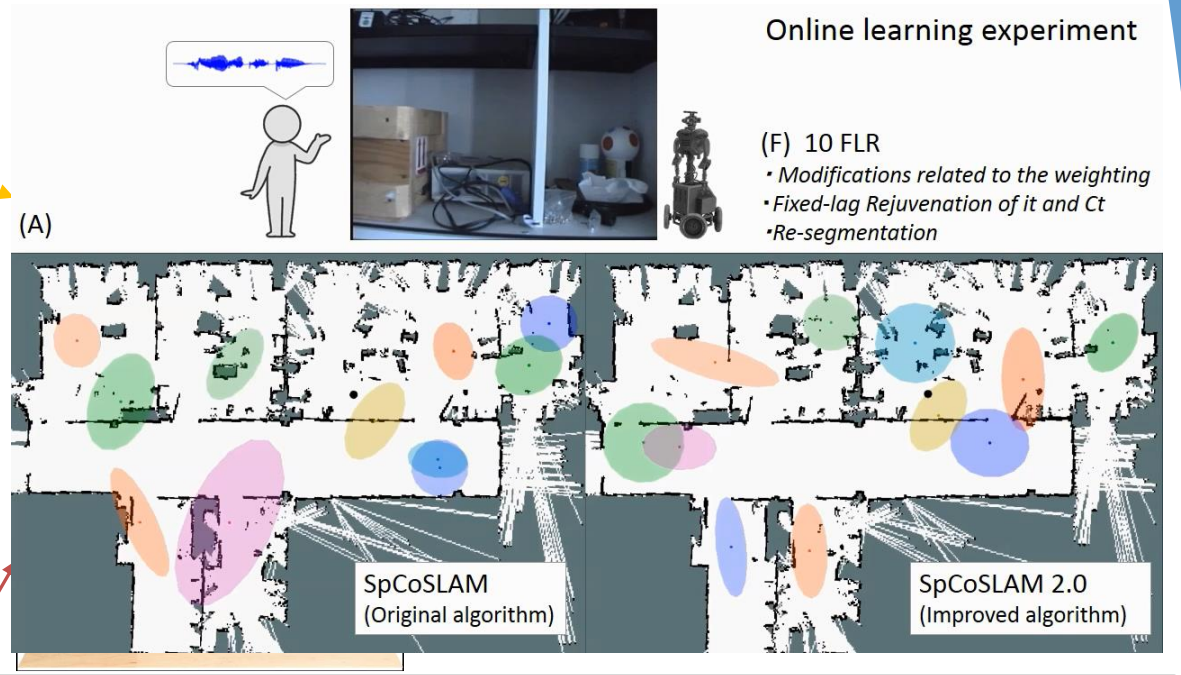
マルチモーダル情報に基づく場所概念

SpCoSLAM [Taniguchi 17]

マルチモーダル情報に基づくノンパラメトリックベイズモデルとSimultaneous Localization And Mapping (SLAM)、語彙獲得の統合モデル

未知環境下からの地図・場所概念・語彙の逐次学習が可能



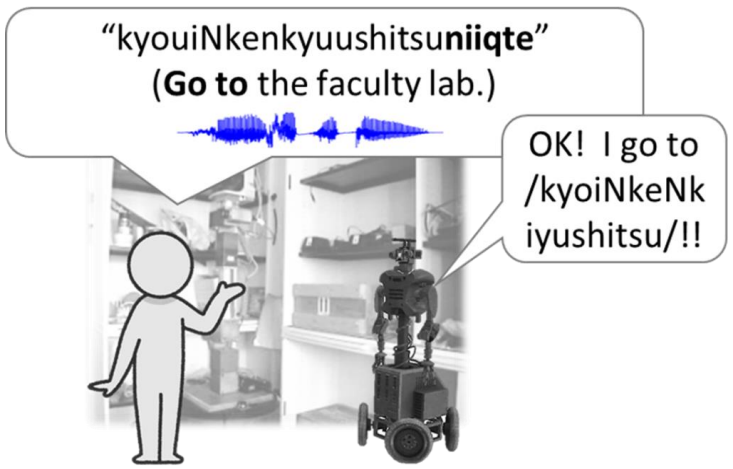


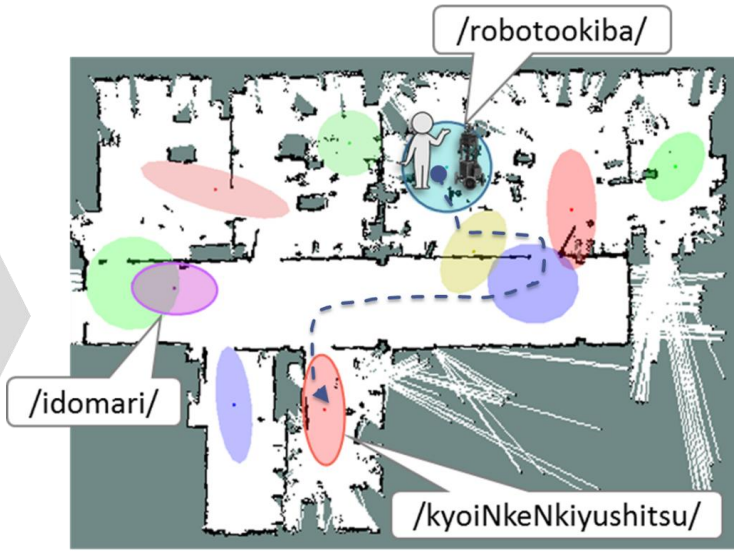
対応する正解音素列 (単語)	i_t	Step 15	i_t	Step 30	i_t	Step 50
/kyouyuuseki/ (共有席)	1	/nobasyanyanamae/ /bawa**kyoo**/ /**yuseki**/	1	/**yuseki**nikibashita/ /**kyoyuseki**/ /**kyoyuseki**dayo/	1	/kibashita/ /ni/ /**kyouyuseki**/
/ikidomari/ (行き止まり)	3	/namaewa/ /enikimashita/ /gonobashiha/	3	/dayo/ /**ikidomari**/ /fokoga/	3	/**idomari**/ /miriiNgusupesu/ /koko/
/roboqtookiba/ (ロボット置き場)	4	/**robotokiba**/ /**robotokiba**nya/ /rimasu/	6	/kochirawaaga**ro**/ /**botoki**/ /baninarimasu/	6	/**wabotookiba**/ /**robotookiba**/ /kochiraga/

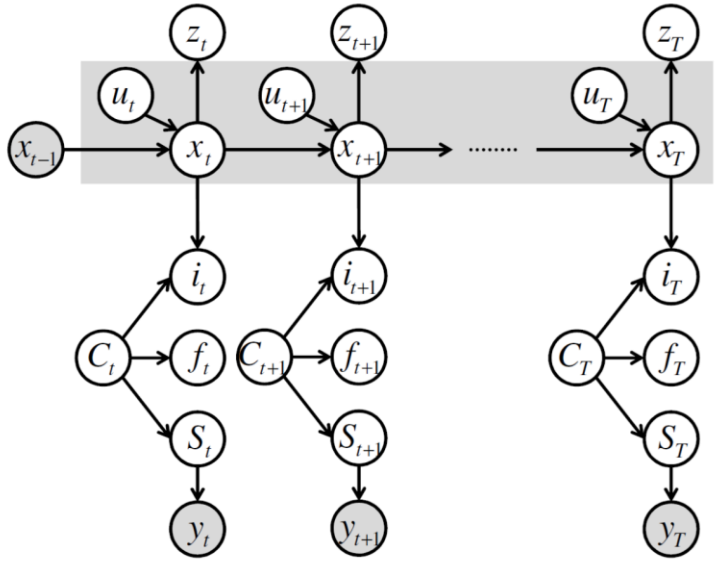
[Taniguchi 17] Taniguchi, A., et al. : Online Spatial Concept and Lexical Acquisition with Simultaneous Localization and Mapping, IEEE/RSJ IROS, pp. 811-818 (2017)

場所概念を用いた確率推論に基づく音声命令からのパスプランニング

- SpCoNavi：確率的生成モデルに基づく音声命令からの経路計画
  - Control as probabilistic inference（確率推論による制御）に基づく軌道の確率推論
  - 音声発話命令 y_t をゴールシグナルを表す観測変数であるとみなす





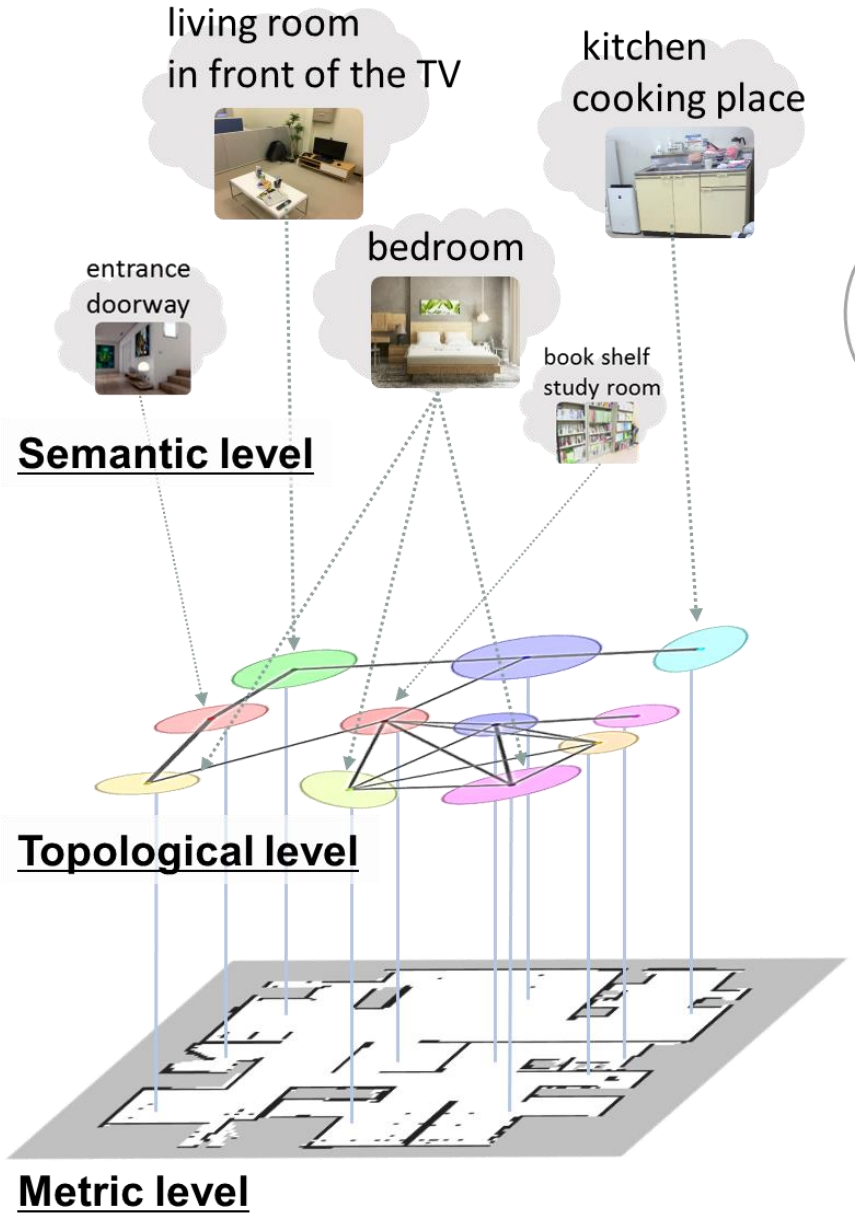


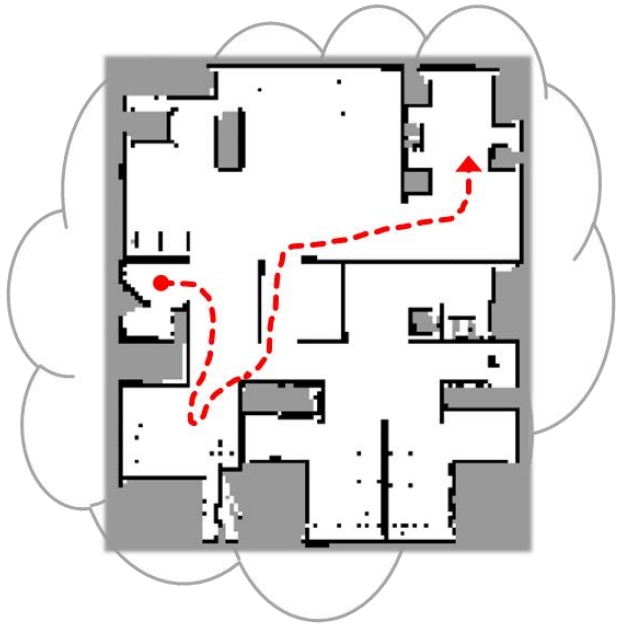
$$u_{1:T} = \underset{u_{1:T}}{\operatorname{argmax}}\, p(\tau \mid y_{1:T}, x_0, \Theta_G)$$

- ロボットが**自律的に獲得した場所の概念・語彙を活用**
- ゴールとして地図上の座標点を指定する必要がなく、**人の音声命令から目的地までのナビゲーション**が可能

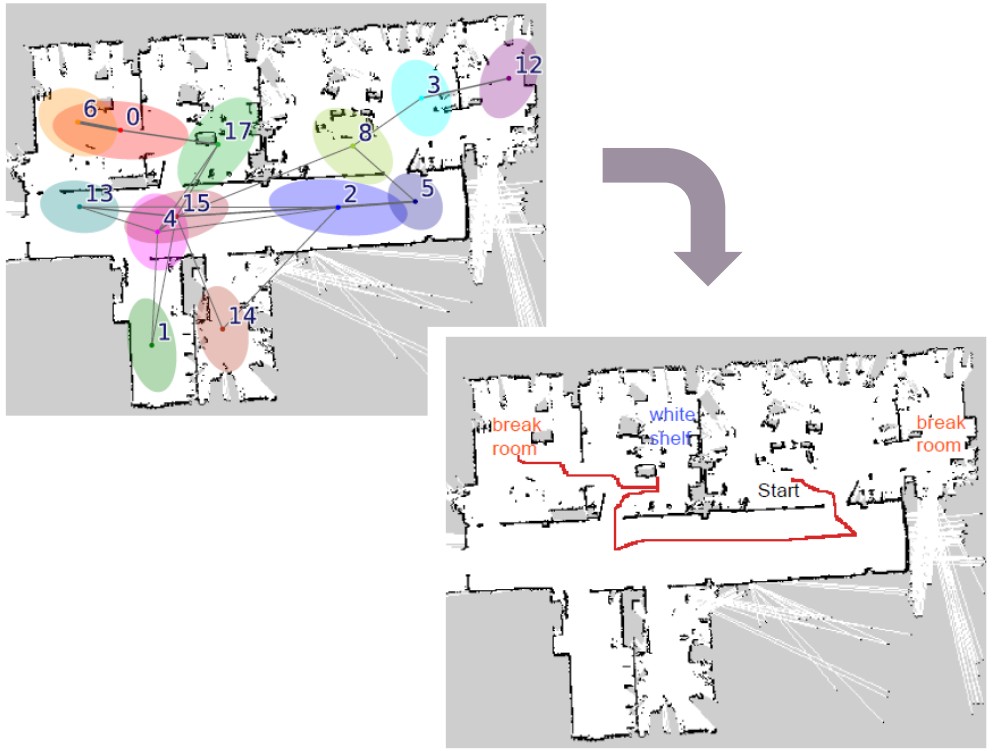
Akira Taniguchi, Yoshinobu Hagiwara, Tadahiro Taniguchi, and Tetsunari Inamura, "Spatial Concept-Based Navigation with Human Speech Instructions via Probabilistic Inference on Bayesian Generative Model." Advanced Robotics, Vol. 34, No.19, pp.1213-1228, Sep, 2020.

Spatial Concept-based Topometric Semantic Mapping for Hierarchical Path-planning from Speech Instructions





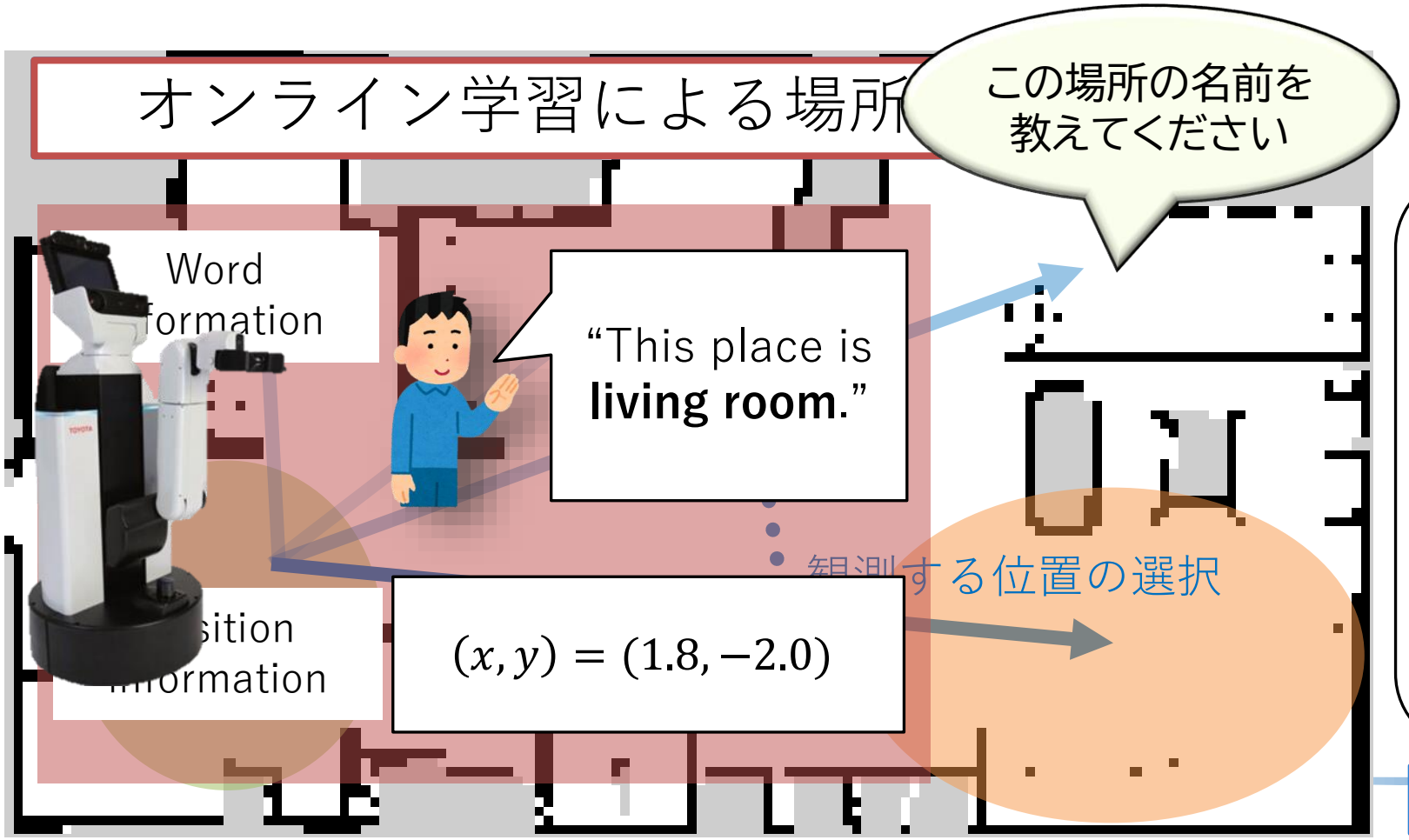
Hierarchical spatial representation provides a mutually understandable form for humans and robots to render language-based navigation tasks feasible.



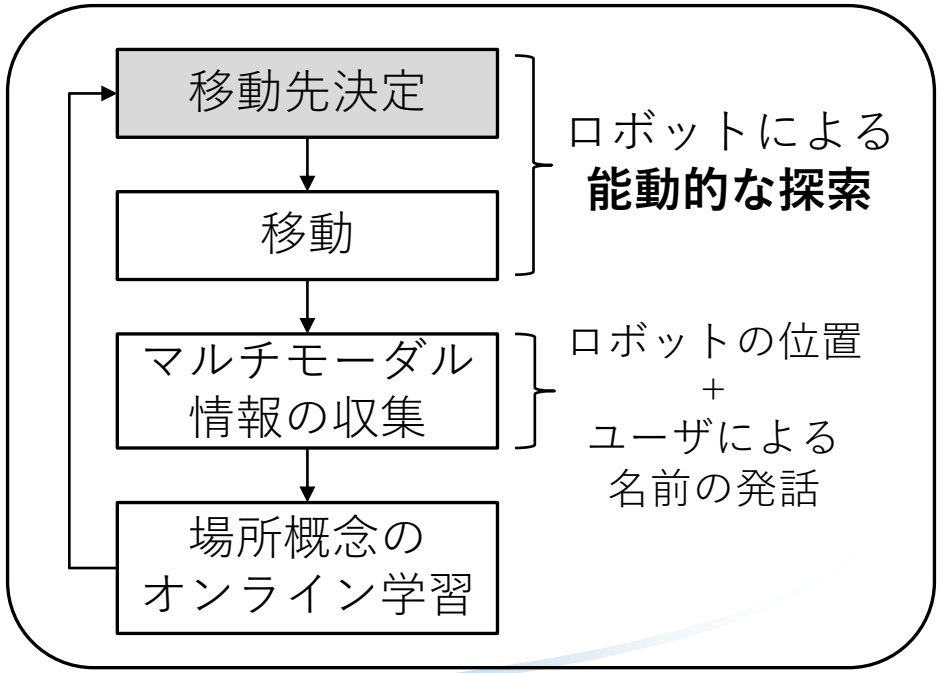
(Preprint)
https://arxiv.org/abs/2203.10820

SpCoAE： Spatial Concept Formation with Information Gain-based Active Exploration

- 場所概念形成の確率的生成モデルにおいて，**パーティクルフィルタよるオンライン学習**と**情報利得(Information Gain; IG) 最大化に基づく能動的な探索**を組み合わせた**能動学習手法 SpCoAE** を提案



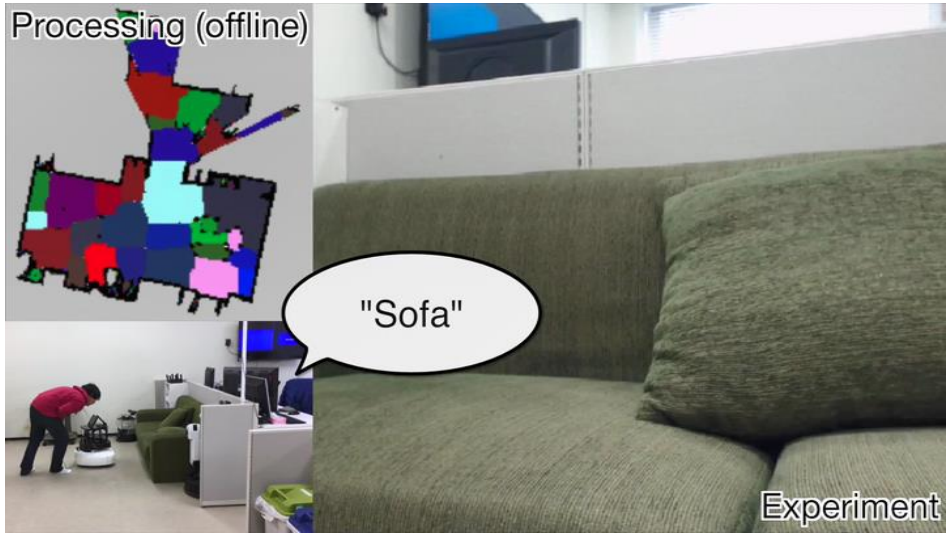
能動的な探索による場所概念形成の流れ



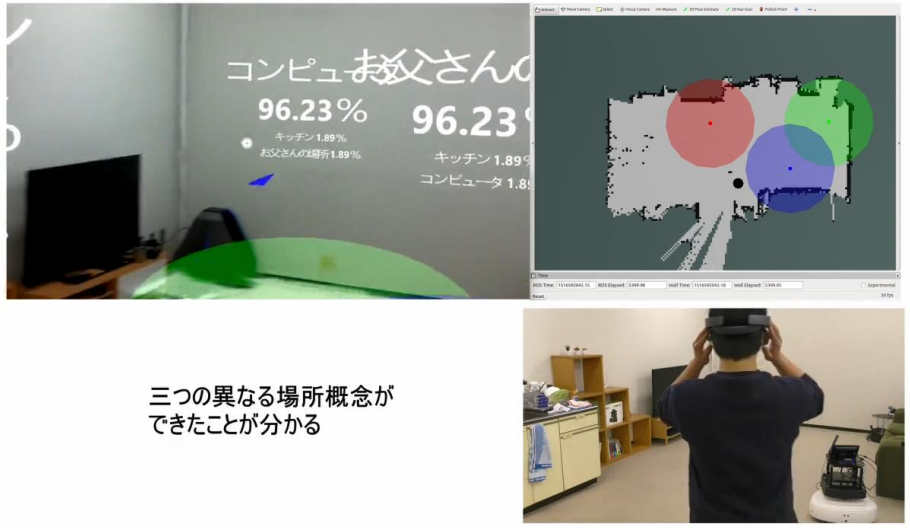
https://arxiv.org/abs/2211.10934

創発システム研究室での取り組み：事例紹介

場所概念に基づく曖昧な命令からの推論



場所概念に基づくセマンティックマッピング



ロボットの内部知識の可視化

場所概念の学習と他の環境への転移

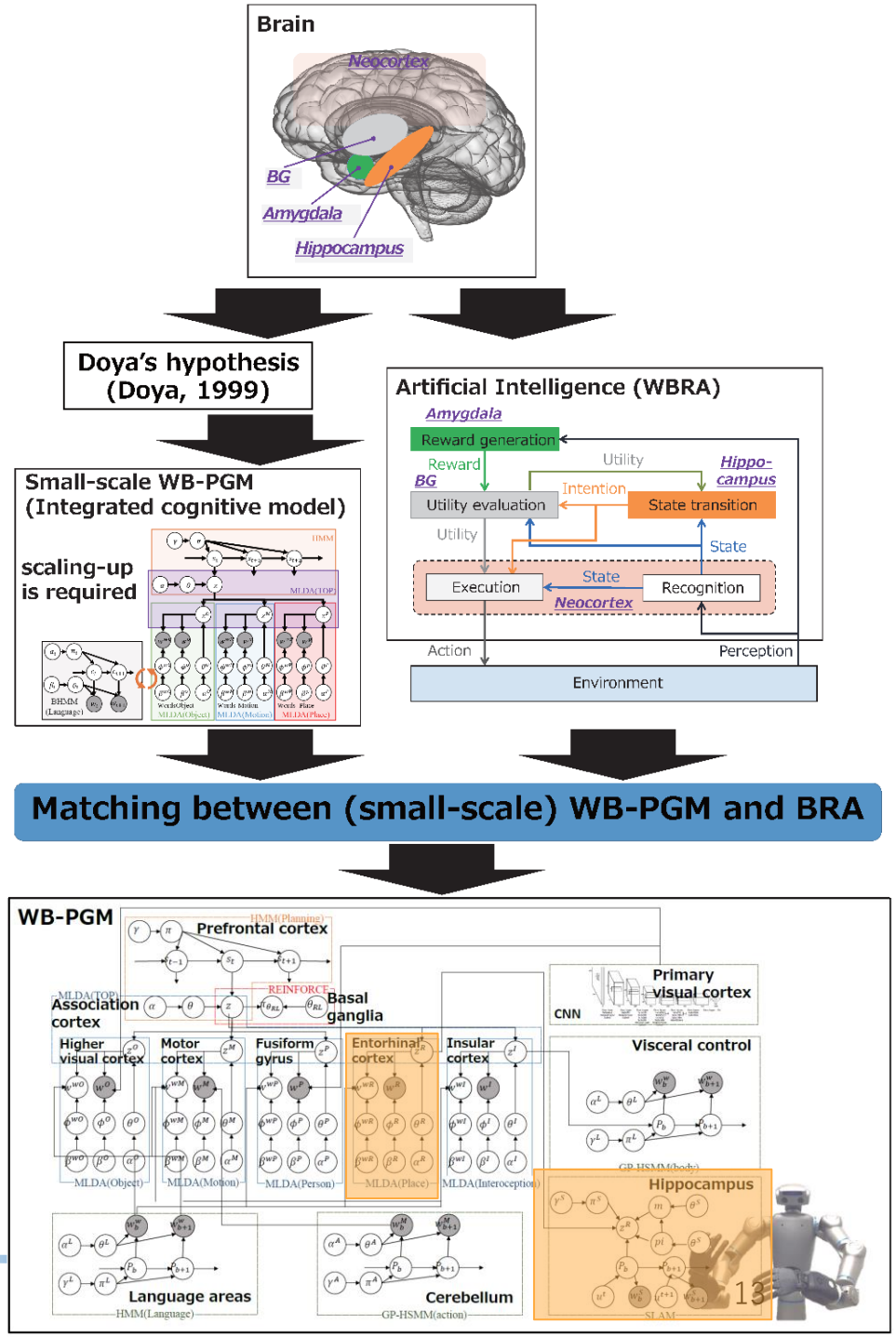
BRAとしての確率的生成モデル（PGM）構築のための変換方法

全脳確率的生成モデル(WB-PGM)

Whole brain Probabilistic Generative Model

- PGMによる全脳アーキテクチャ構成のためのパースペクティブ論文 [Taniguchi et. al., 2021]
- **目的**
  - 汎用人工知能（AGI）の実現
  - 人の脳に学び、脳を模した認知アーキテクチャの構築
  - 確率的生成モデルを用いた統合的認知システムの構築
- **Research Question**
  - どのような認知モジュールを実装するべきか？
  - それらをどのように統合させ連携されればよいか？
- 以下の2つのアプローチを組み合わせることで、これらの疑問に答える。
  1. **脳にインスパイアされたAI**：人間レベルの知能を創り出すために、人間の脳アーキテクチャから学ぶこと
  2. **PGMベースの認知システム**：発達ロボティクスにおける構成論的アプローチとしてPGMを統合した統合的認知システムを開発すること

今回の講演内容は、ここからのスピンオフ



Taniguchi, T., Yamakawa, H., Nagai, T., Doya, K., Sakagami, M., Suzuki, M., Nakamura, T., & Taniguchi, A. (2021). Whole brain Probabilistic Generative Model toward Realizing Cognitive Architecture for Developmental Robots. In *arXiv [cs.AI]*. http://arxiv.org/abs/2103.08183（Neural Networks誌 査読中）

確率的生成モデルとは？

Probabilistic generative model (PGM)

- データが生成される過程をモデル化したもの
- 確率分布を仮定することでデータの統計的な性質をとらえる
- グラフィカルモデルによってモデル構造を可視化できる
- グラフィカルモデル
  - 変数間の依存関係をグラフ構造で表現
  - ノード：確率変数
  - エッジ：依存関係

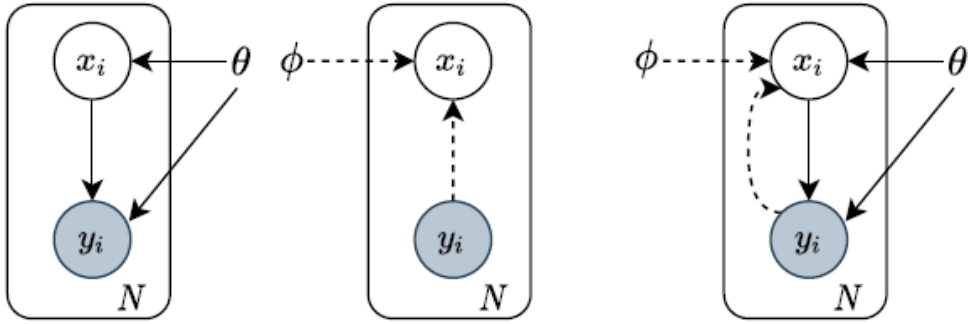
生成モデル

$x_i \sim p(x_i|\theta) \quad = p_\theta(x_i)$

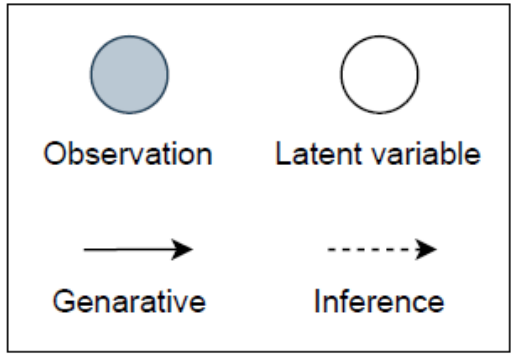
$y_i \sim p(y_i|x_i,\theta) \quad = p_\theta(y_i|x_i)$

推論モデル

$q(x_i|y_i,\phi) = q_\phi(x_i|y_i)$

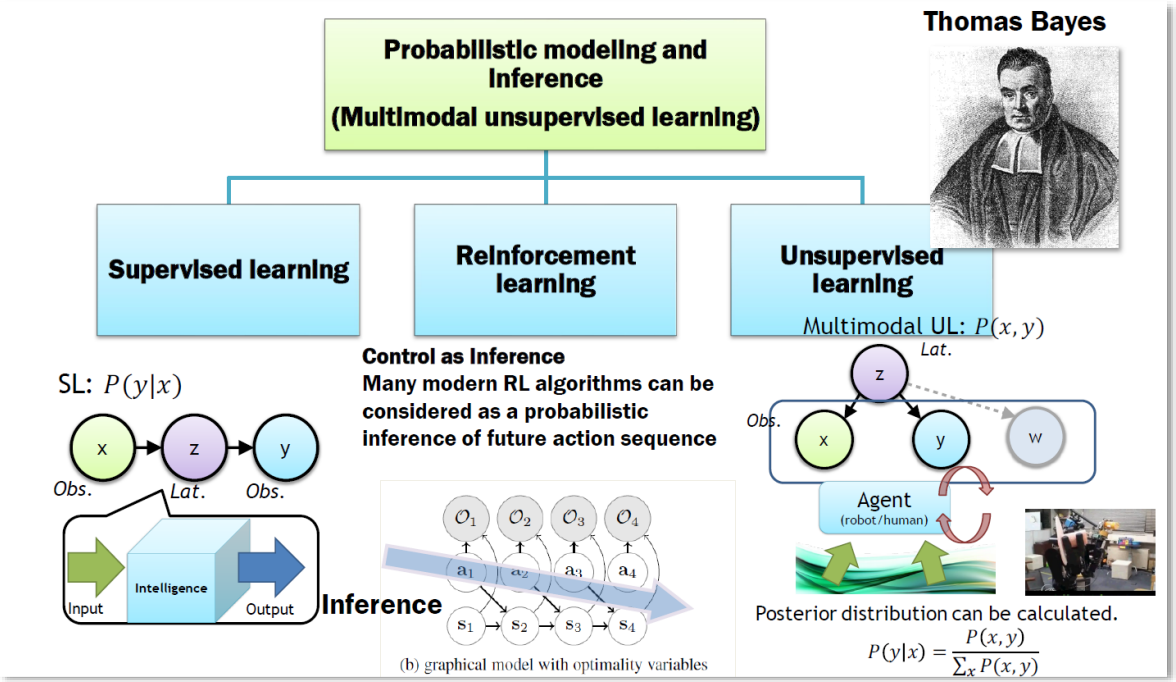


(a) 生成モデル　(b) 推論モデル　(c) 両方（VAE）



なぜ確率的生成モデル？

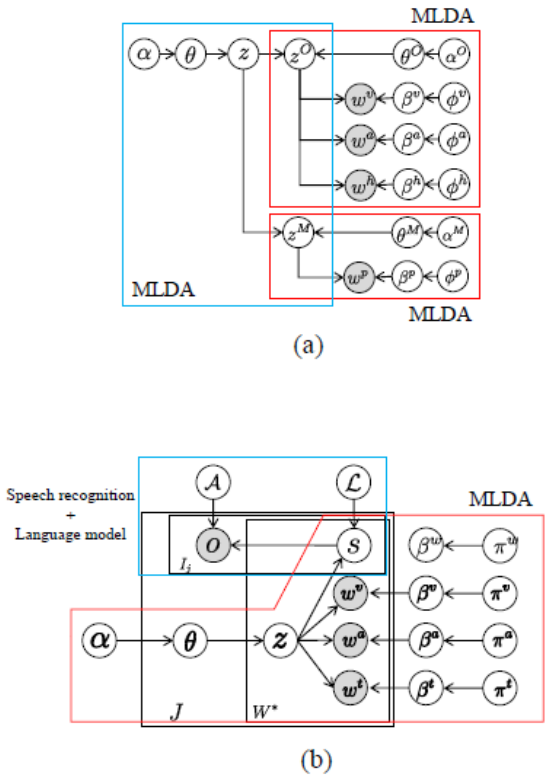
- グラフィカルモデルによって構造を容易に可視化できる
- PGM同士を統合しやすい（Neuro-SERKETフレームワーク [Taniguchi 2020] ）
  - ➢ 全脳PGM へ
- 教師あり学習、教師なし学習、強化学習をすべてPGMの上で議論できる
- 神経科学分野などでも議論・理論構築されている
  - ベイズ脳仮説 [Doya 2007]
  - 自由エネルギー原理/予測符号化仮説 [Friston 2012]
  - 世界モデル（World model）

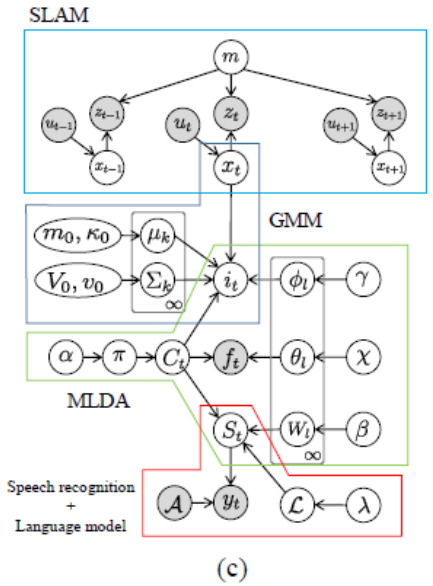


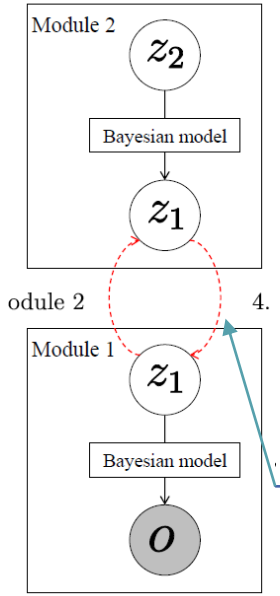
↑谷口忠大先生スライドより

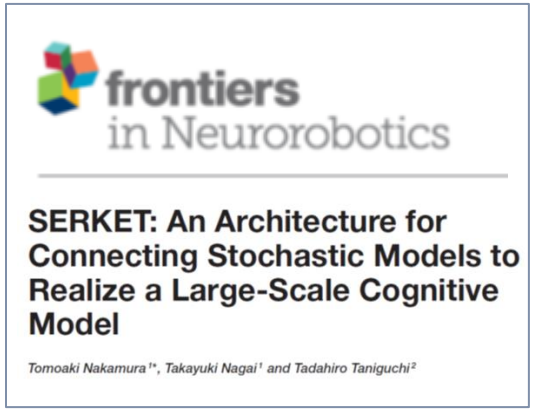
[Taniguchi 2020] Tadahiro Taniguchi, Tomoaki Nakamura, Masahiro Suzuki, Ryo Kuniyasu, Kaede Hayashi, Akira Taniguchi, Takato Horii, and Takayuki Nagai, “Neuro-SERKET: Development of Integrative Cognitive System through the Composition of Deep Probabilistic Generative Models”, New Generation Computing, Jan. 2020.
[Doya 2007] Doya, K., Ishii, S., Pouget, A., Rao, R.P.N., Bayesian Brain: Probabilistic Approaches to Neural Coding. MIT Press. 2007.
[Friston 2012] Friston, Karl, and Ping Ao. "Free energy, value, and attractors.“ Computational and mathematical methods in medicine 2012.

Neuro-SERKET: Development of Integrative Cognitive System Through the Composition of Deep Probabilistic Generative Models [Taniguchi+ 20]









1. Belief propagation
2. SIR
3. MH

複雑な認知システムを
効率的に開発可能に

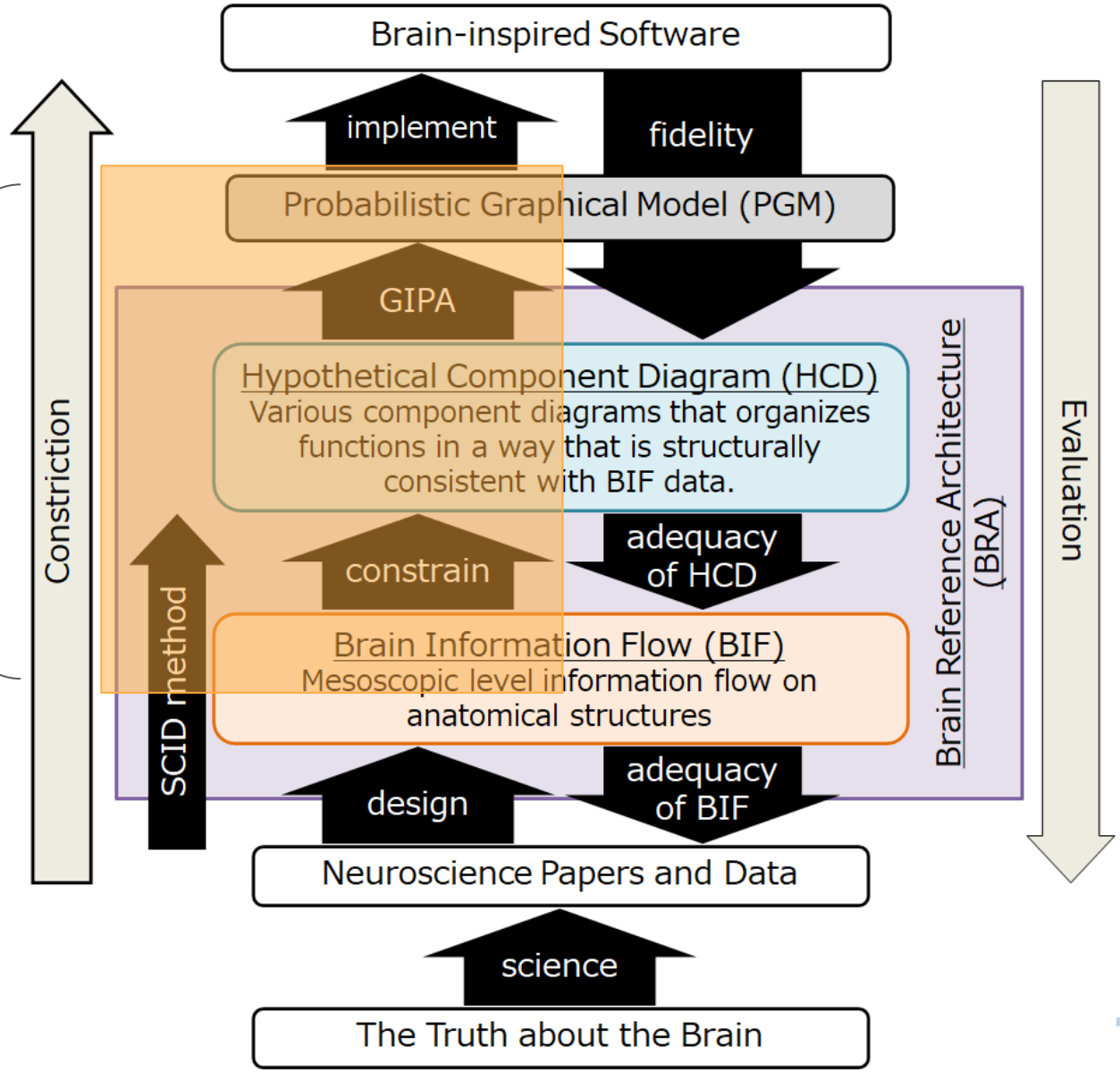
- Connecting cognitive modules developed as probabilistic generative models and letting them work together as a single unsupervised learning system.
- Having inter-module communication of probabilistic information and guaranteeing theoretical consistency to some extent.
- Neuro-SERKET supports deep generative models, i.e., VAE, as well.

Nakamura T, Nagai T and Taniguchi T, SERKET: An Architecture for Connecting Stochastic Models to Realize a Large-Scale Cognitive Model. Front. Neurorobot. 12:25. (2018) doi: 10.3389/fnbot.2018.00025

Taniguchi, T., Nakamura, T., Suzuki, M. et al. Neuro-SERKET: Development of Integrative Cognitive System Through the Composition of Deep Probabilistic Generative Models. New Gener. Comput. 38, 23–48 (2020). https://doi.org/10.1007/s00354-019-00084-w

本レクチャーの全体構成

足場の上にPGMを構築する(谷口)
- PGM作成(GIPA)
- HCD作成



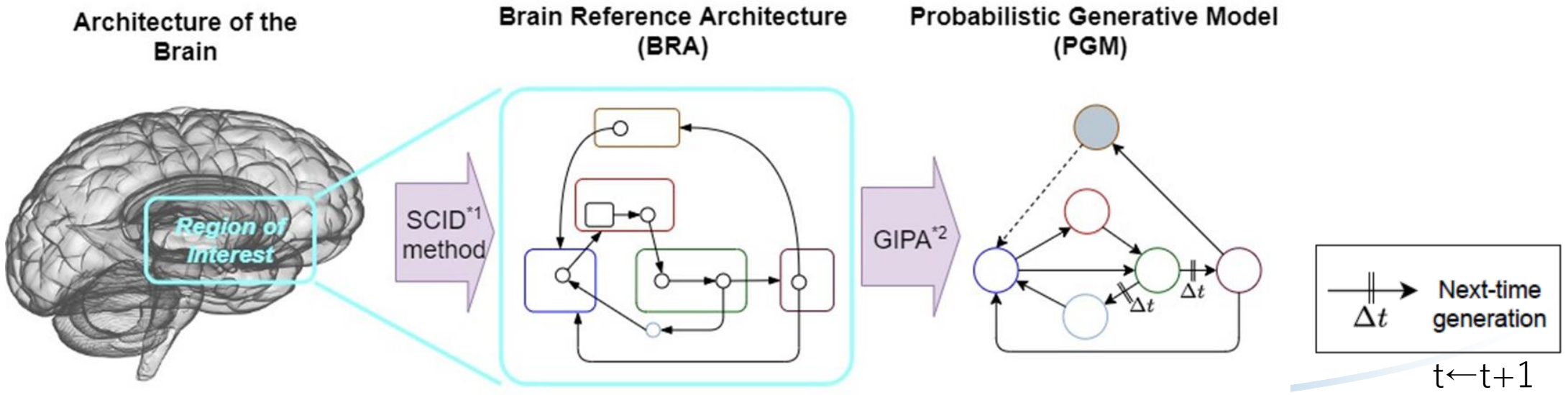
GIPA: Generation-inference process allocation

- 脳部位の解剖学的構造を生成モデルの変数の依存関係へ変換
- PGMの制約
  - Directed acyclic graphsである必要性（ループを作れない）
- 基本的なGIPAの手順
  1. エッジを**生成モデルと推論モデルに分ける**（Table 1を主な基準とする）
  2. **次時刻生成(Δt)の表現を導入する**

Table 1: Counter stream pathways in neocortex

Pathways	Feedforward	Feedback
Direction	From the outside world to the internal state (from lower to higher area)	From the internal state to the outside world (from higher to lower area)
Laminar on cortical microcircuits (Markov et al., 2014, 2013)	Layer 3, and Layer 4	Layer 2
Meaning of signals (Yamakawa, 2020)	Observation	Prediction
Graphical model representation of PGM	inference process	generative process

WB-PGM論文より



GIPA: Generation-inference process allocation

- 1．エッジを生成モデルと推論モデルに分ける（数理・理論として）
  - Amortized (variational) inference
    - 生成モデルとは別に推論モデルの接続構造を定義できる
    - 推論モデルをNeural networkなどの関数で近似
    - Auto-Encoding Variational Bayes (AEVB)
      - Variational Auto-Encoder (VAE)が代表的

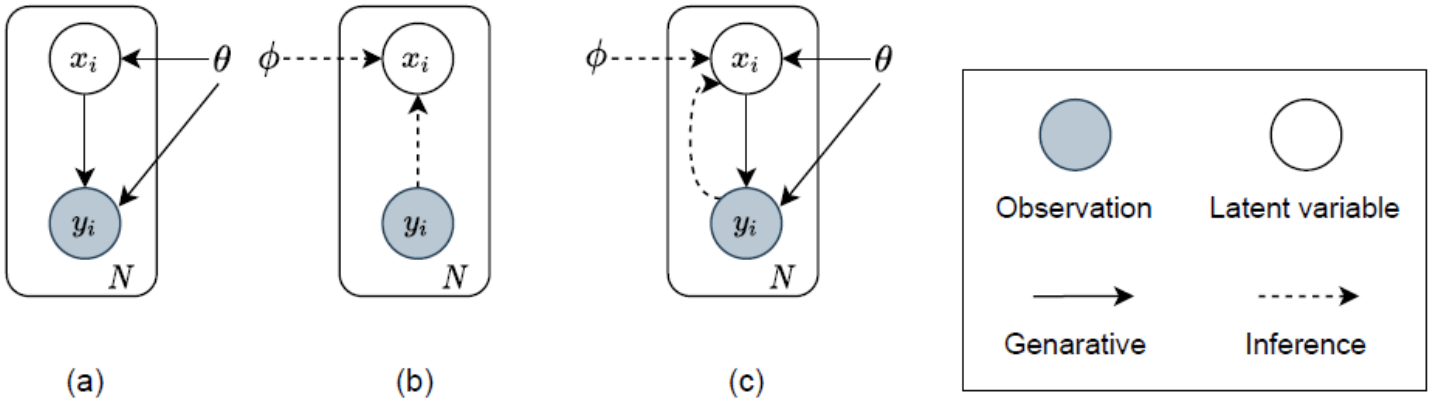
生成モデル

$x_i \sim p(x_i|\theta) \quad = p_\theta(x_i)$

$y_i \sim p(y_i|x_i,\theta) \quad = p_\theta(y_i|x_i)$

推論モデル

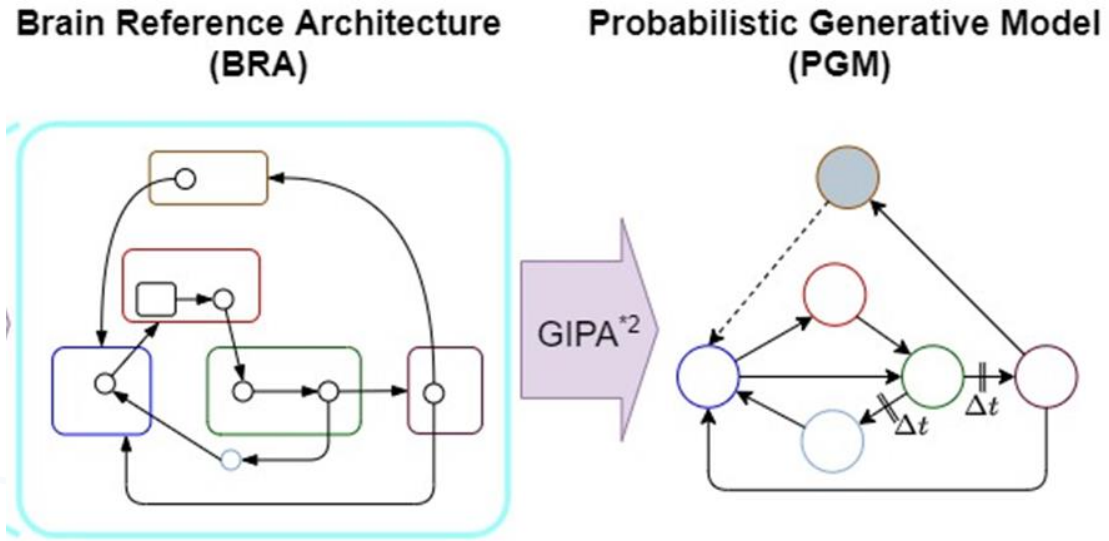
$q(x_i|y_i,\phi) = q_\phi(x_i|y_i)$



Kingma, D. P., &Welling, M. (2014). Stochastic gradient VB and the variational auto-encoder. In Second International Conference on Learning Representations, ICLR.
Murphy, K. P. (2012). Machine learning: a probabilistic perspective. Cambridge, MA: MIT Press.

GIPA: Generation-inference process allocation

- ２．次時刻生成($\boldsymbol{\Delta t}$)の表現を導入する
  - 問題： Δtを（ループの中の）どこにどう導入するか
  - 決め方
    - Δtの時間幅がどのくらいの周期なのか（ループの周期）を考えつつ決める
    - 解剖学的・神経科学的な知見から、過去や未来に関する情報をコーディングしているノードがあれば、それを参考に決める
    - 解剖学的・神経科学的な知見から、時間遅れが発生すると思われるノードがあれば、それを参考に決める
  - 制約
    - 時間展開した時に一意にPGMが決まるようにする
    - Δtが複数ある場合、時刻の同期が取れるようにする
    - １ループに対して基本的には一つのΔtが割り当たる



Hippocampal formation-inspired probabilistic generative model

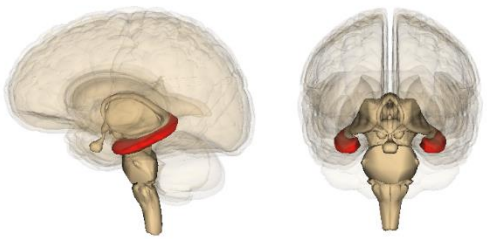
HF-PGM：海馬体の確率的生成モデル

Akira Taniguchi, Ayako Fukawa, Hiroshi Yamakawa, "Hippocampal formation-inspired probabilistic generative model", Neural Networks, Vol.151, No. July, pp.317-335, 2022. DOI: 10.1016/j.neunet.2022.04.001
https://www.sciencedirect.com/science/article/pii/S0893608022001332

なぜ海馬体なのか

海馬体：脊椎動物の記憶を司る脳部位

空間学習や空間探索といった空間記憶に深く関わる



認知的処理を担うコア領域

脳型の汎用人工知能の構築に不可欠の構成要素

海馬体に関する数多くの神経科学知見が蓄積されている

あたりをつける：海馬体の神経科学的知見

海馬体

脊椎動物の記憶を司る脳部位．空間学習や空間探索といった空間記憶に深く関わる認知的処理を担うコア領域
脳型の汎用人工知能の構築に不可欠の構成要素．海馬体に関する数多くの神経科学知見が蓄積されている

ナビゲーション

- 動物が空間内で環境情報を取得しながら適切な経路を選択して目的地に到達する行動

認知地図

- ”動物は環境の空間的位置関係についての地図を探索によって形成し，この地図を利用して行動している”という考え

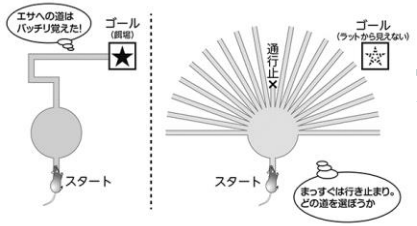
自己位置推定

- ナビゲーションの実行や認知地図の形成の前提として，常に動物が現在の位置を認識する能力

経路統合(path integration: PI)

- 自己の運動情報などの移動情報を統合して自己位置を計算する機能

自己位置推定のための方法の一つ



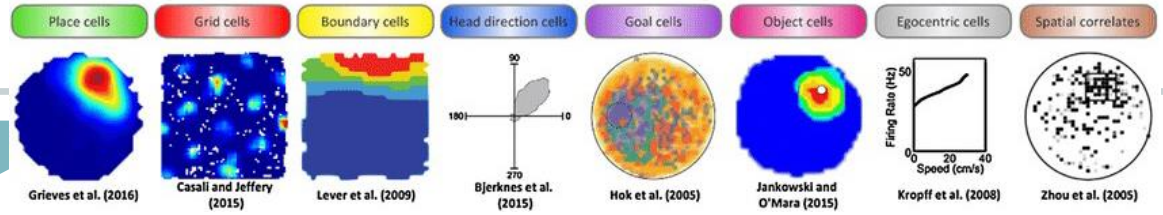
引用元：
https://cbs.riken.jp/jp/public/tsunagaru/fujisawa/02/

■場所細胞(Place cells)：環境の特定の場所にいるときに発火する
げっ歯類の海馬で発見された

■格子細胞(Grid cells)： 場所細胞と同様に動物が環境の特定の場所にいるときに発火する
げっ歯類の内側嗅内皮質(medial entorhinal cortex: MEC)で発見された
経路統合の実行に関わるとされている

■頭方位細胞(Head-direction cells)：場所に関係なく頭が特定の方向に向いているときにだけ活動する

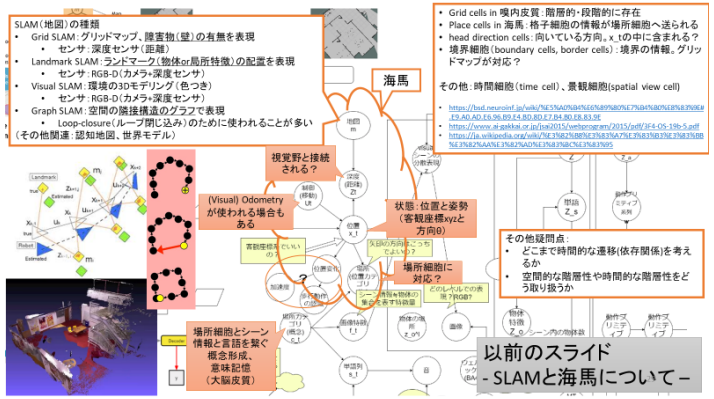
■スピード細胞(Speed cells)：個体の移動速度に依存した活動を示す



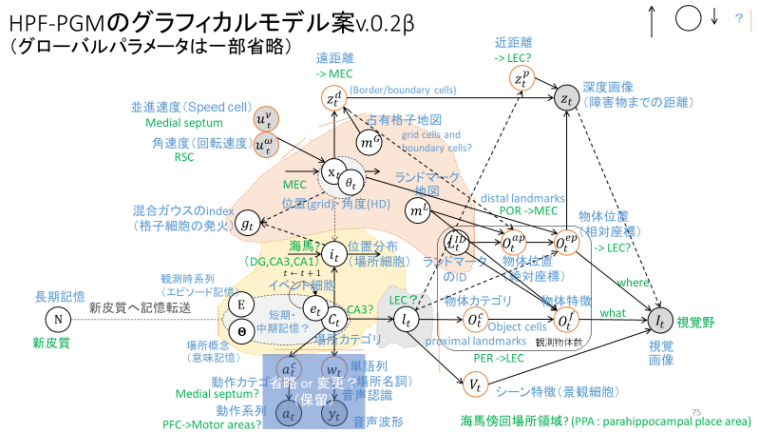
哺乳類においては海馬体がナビゲーションや認知地図の形成等に重要な役割を果たしていると考えられている
場所細胞・格子細胞が空間的な認知処理機能の実行に関わるとされている

構築の経緯：モデル

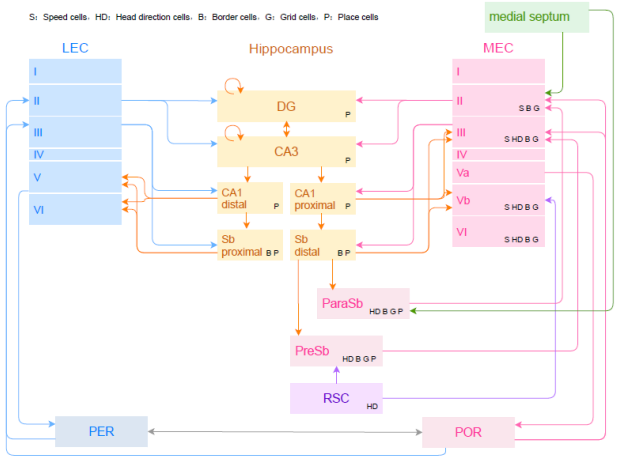
WB-PGMの議論での初期案と疑問提示



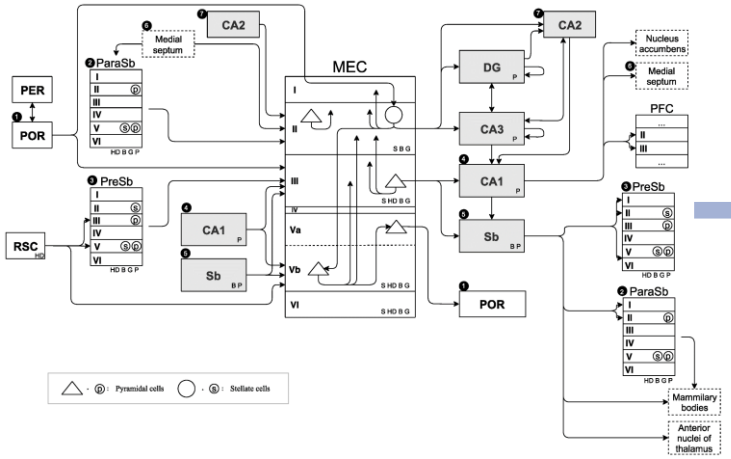
SpCoSLAMのPGMを分解・拡張



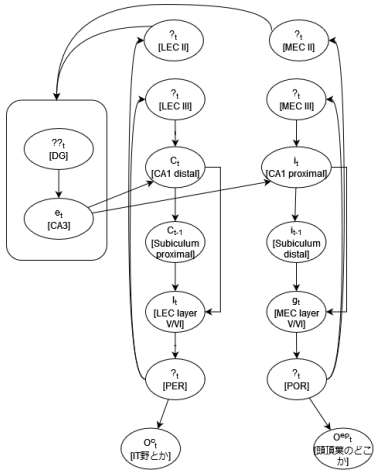
作成した海馬体のBIF

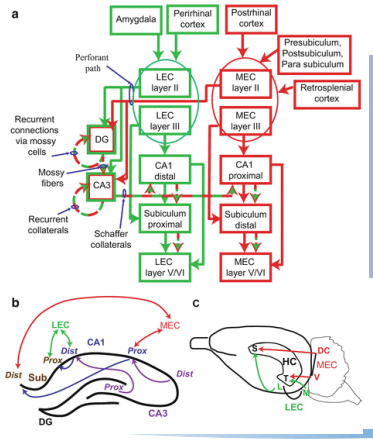


海馬体のBIF [Fukawa et al., 2020]

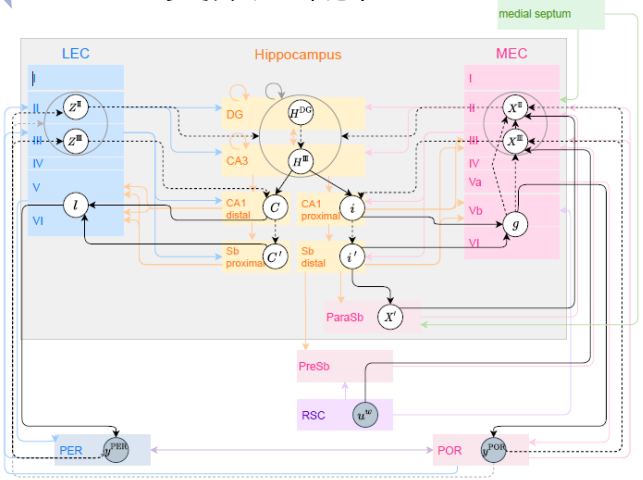


LECとMECの解剖学的構造（右）と対応付けたPGM案（左）





BIF上に変数を配置したHF-PGM

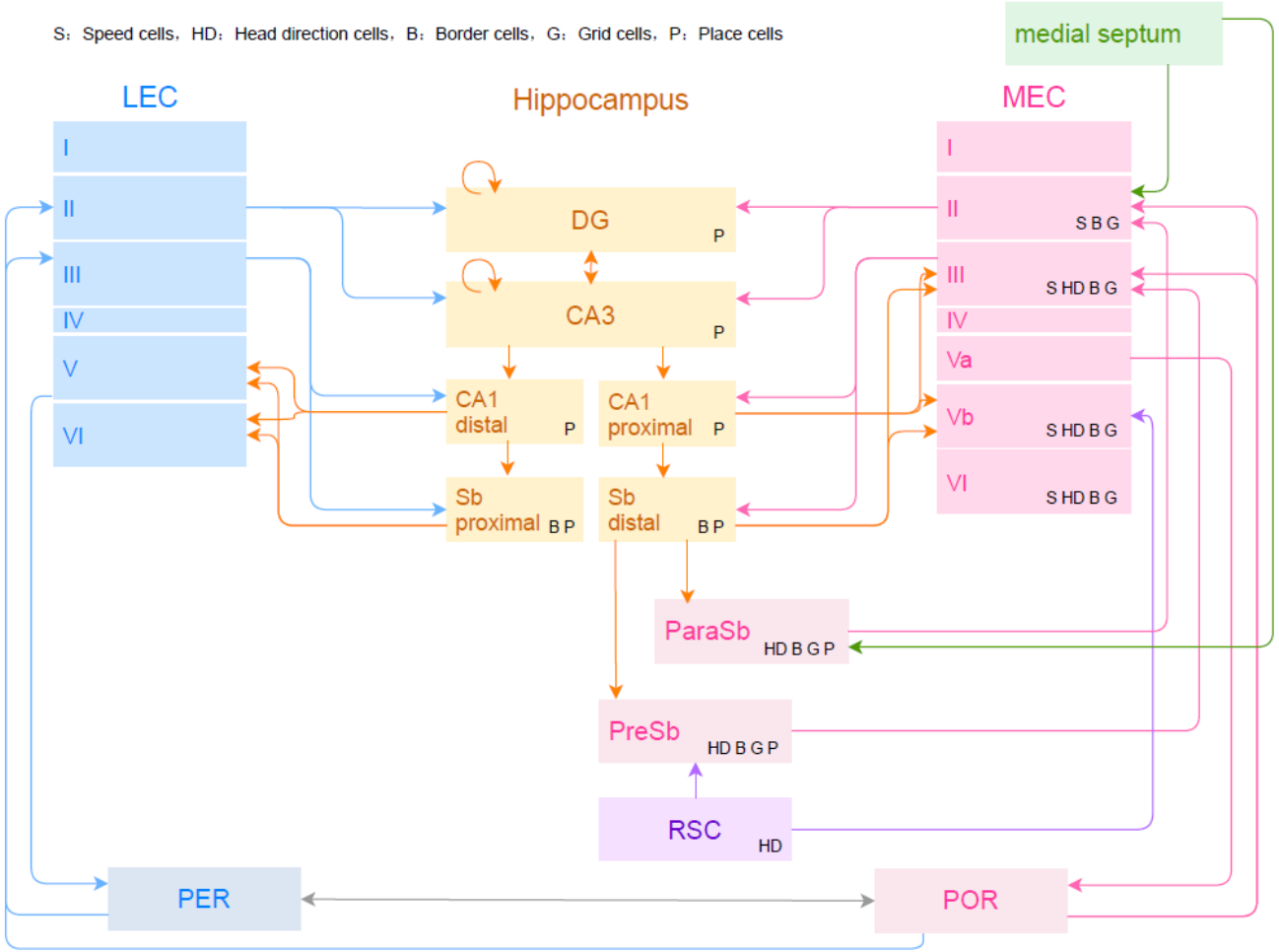


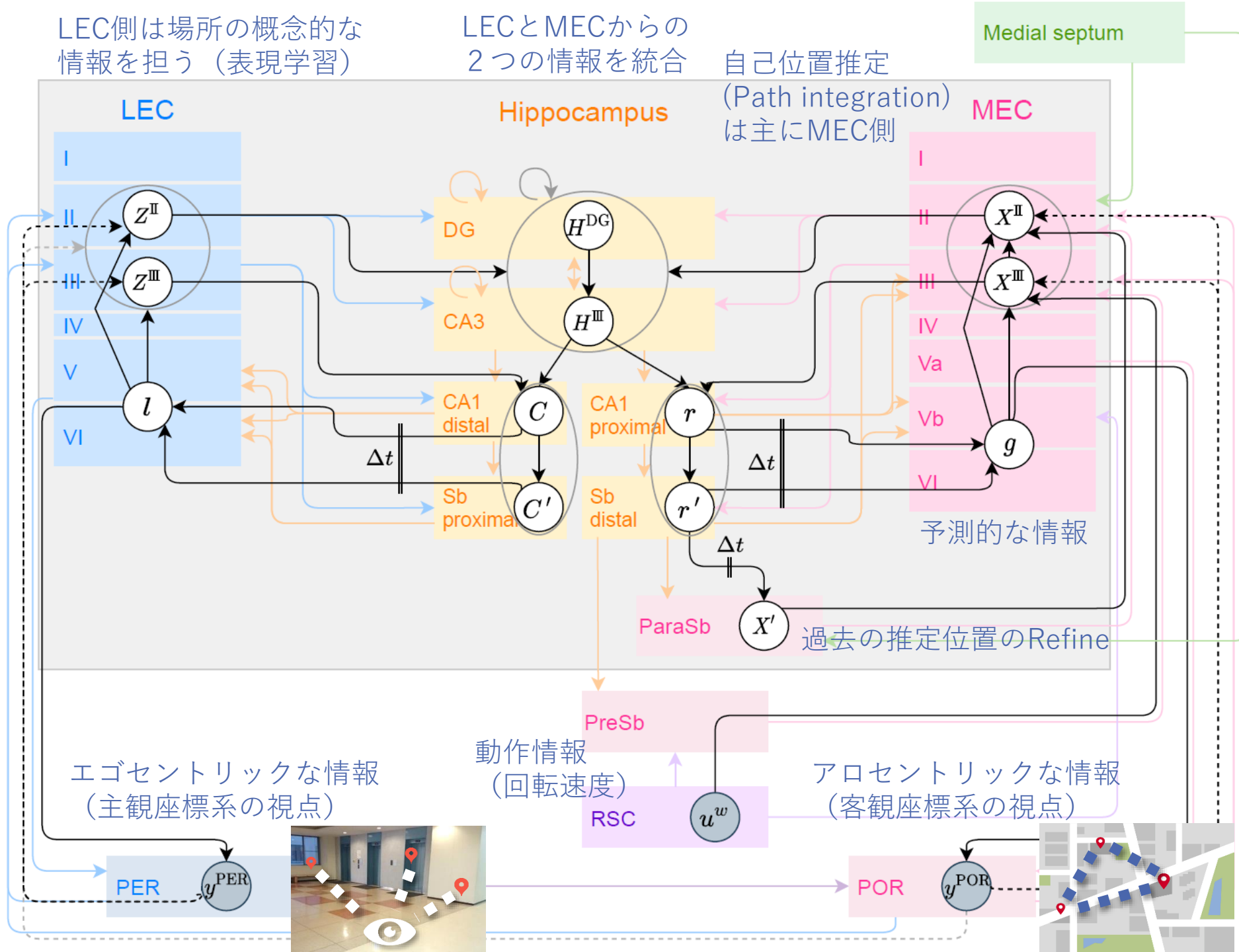
Fukawa, A., Aizawa, T., Yamakawa, H., & Yairi, I. E. (2020). Identifying core regions for path integration on medial entorhinal cortex of hippocampal formation. Brain Sciences, 10 .

Region-of-interest, input/output, and top-level function

- Region-of-interest
  - LEC, MEC, CA1, CA3, DG, Sb, ParaSb
  - ROIに隣接する領域: PreSb, POR, PER, RSC
- Input/output
  - Input: POR, PER, and RSC
  - Output: the predicted values of POR and PER at the next time step
- Top-level function
  - (i) **Self-localization** (path integration and observational correction)
  - (ii) **Place categorization** by integrating allocentric and egocentric information

脳情報フロー (Brain Information Flow: BIF)

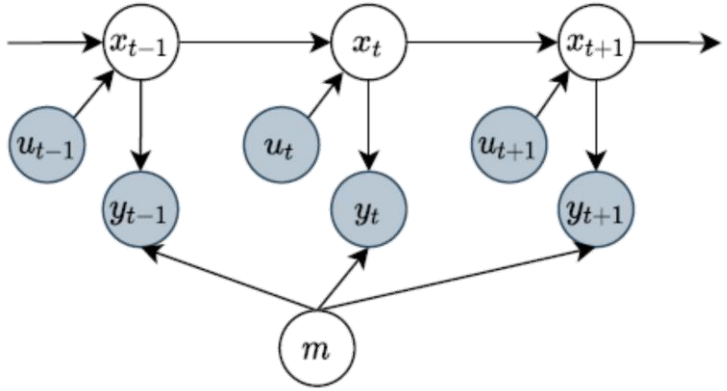




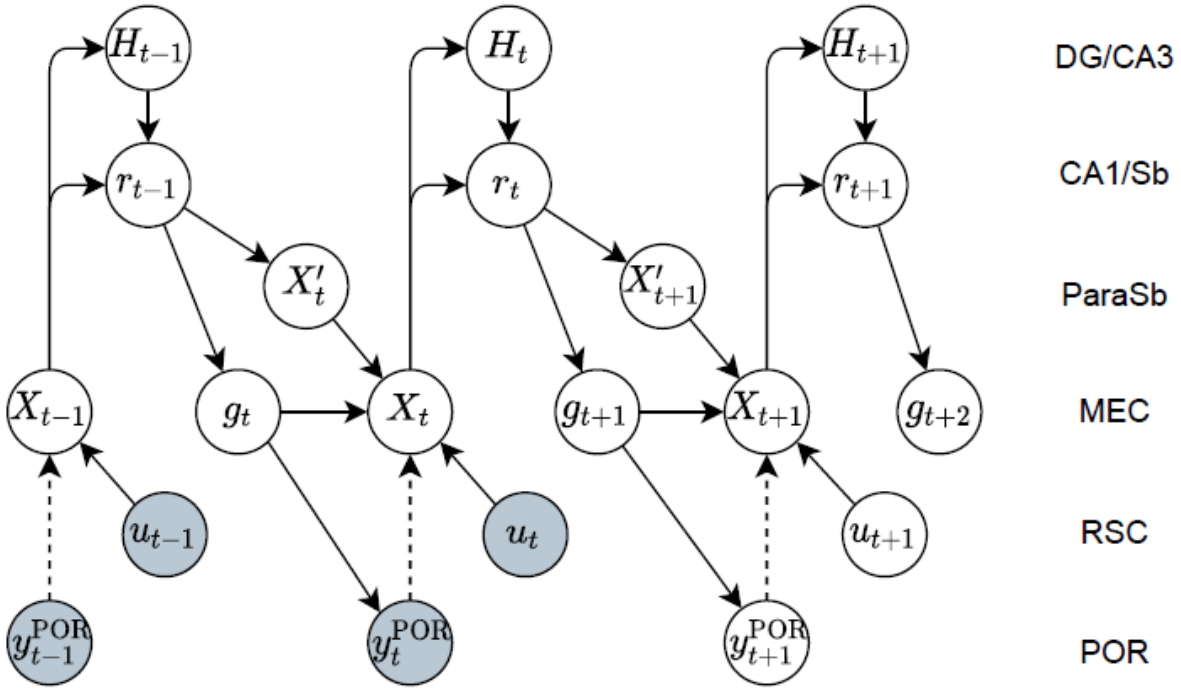
Symbol	Function of components on HCD
C	Place category (internal representation of visual spatial information)
r	Position distribution (cluster information regarding positions)
C'	Place category at the previous time
r'	Position distribution at the previous time
H^{III}	Integrated semantic memory and episodic memory of information from X and Z
H^{DG}	Integrated semantic memory
X^{II} ($\{x_t\}$)	Self-position information, predictive distribution
X^{III} ($\{x_t\}$)	Self-posture information (position and orientation), observation likelihood
g	Predictive representation of X (Prediction at future time regarding movement/speed amount or posture)
Z^{II}	Abstraction of information from y^{PER} (transmission of prediction, generation of prediction signal)
Z^{III}	Abstraction of information from y^{PER} (Observation transmission)
l	Predictive representation of Z (Prediction at future time from the difference between C' and C)
X' ($\{x_{t-1}\}$)	Self-posture information
y^{POR} ($\{y_t\}$)	Allocentric visual information (distal distance/landmarks, absolute object positions)
y^{PER}	Egocentric visual information (proximal distance/landmarks, relative object positions, object category, landscape information)
u^w ($\{u_t\}$)	Rotational speed movement

時間遷移のグラフィカルモデル（MEC側のみ）

- SLAMのPGMの拡張として表現される
- LEC側は省略している
- SLAMのPGMとの差異
  - 潜在変数が細かく段階的に分けられている
  - 時間差分情報を保持・利用
  - 次時刻の観測の予測値を生成する
    - Predictive coding

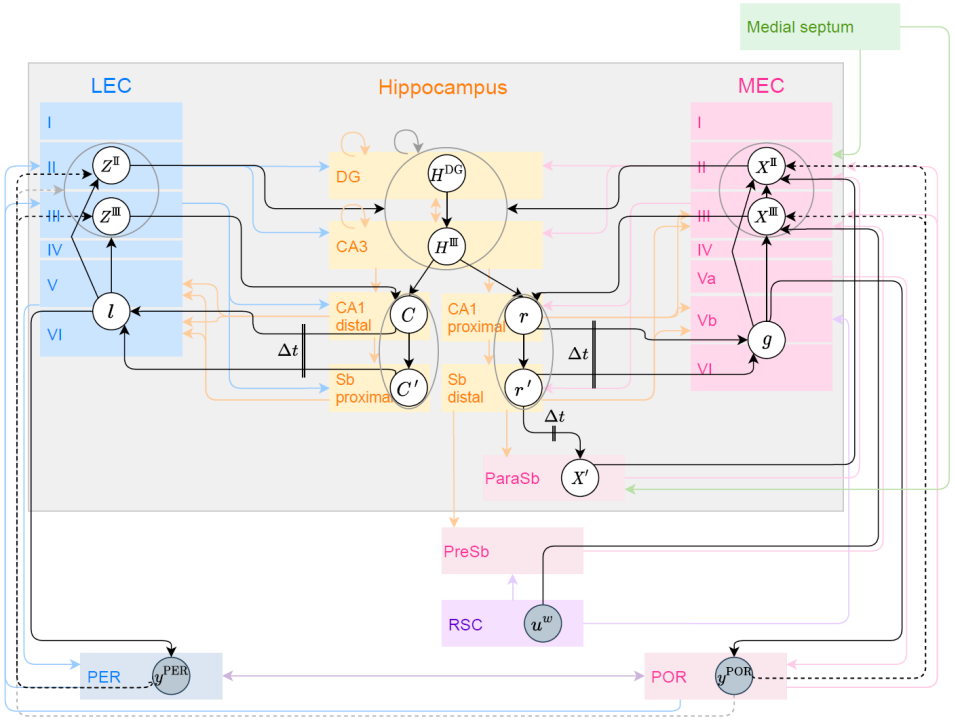


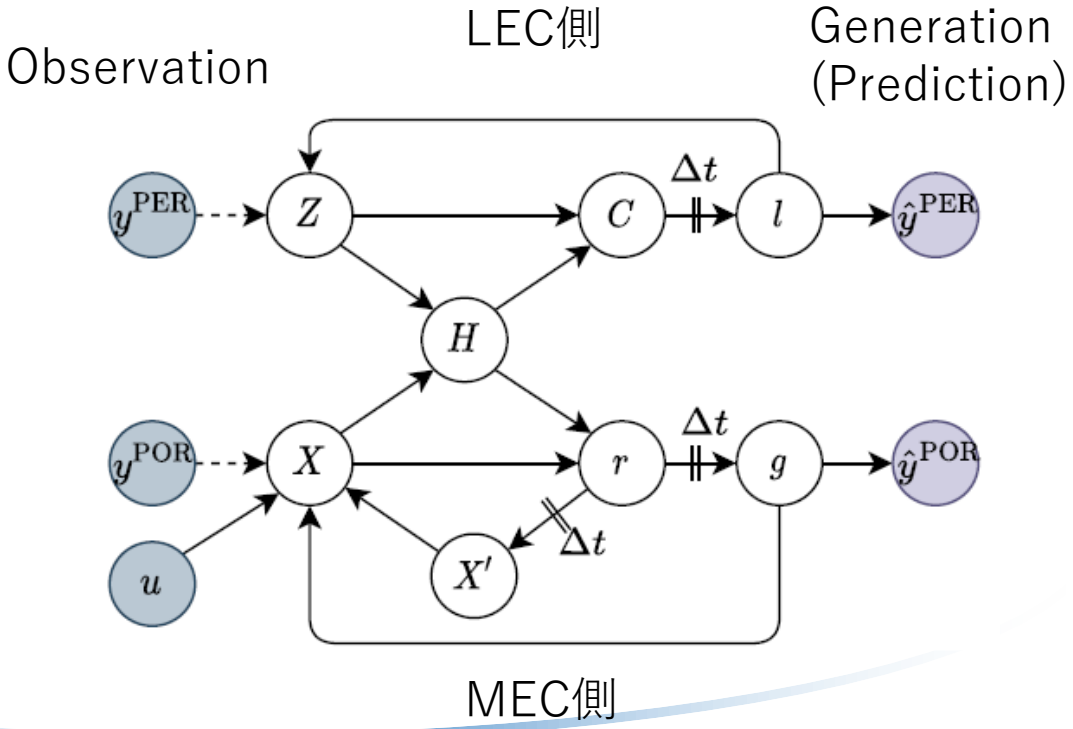
- Variables
  - X_t: Self-position
  - X'_t: Predicted self-position
  - r_t: Cluster information regarding positions
  - H_t: Integrated higher-level internal
  - representation
  - g_t: Prediction at future time regarding
  - movement/speed amount or posture
  - y_t: Input/output variables
  - u_t: Rotational speed movement



Encoder-decoder表現のグラフィカルモデル

- リカレント構造付きのマルチモーダルEncoder-decoderモデルの拡張形として表せる
  - 観測値と予測値を分けて表現



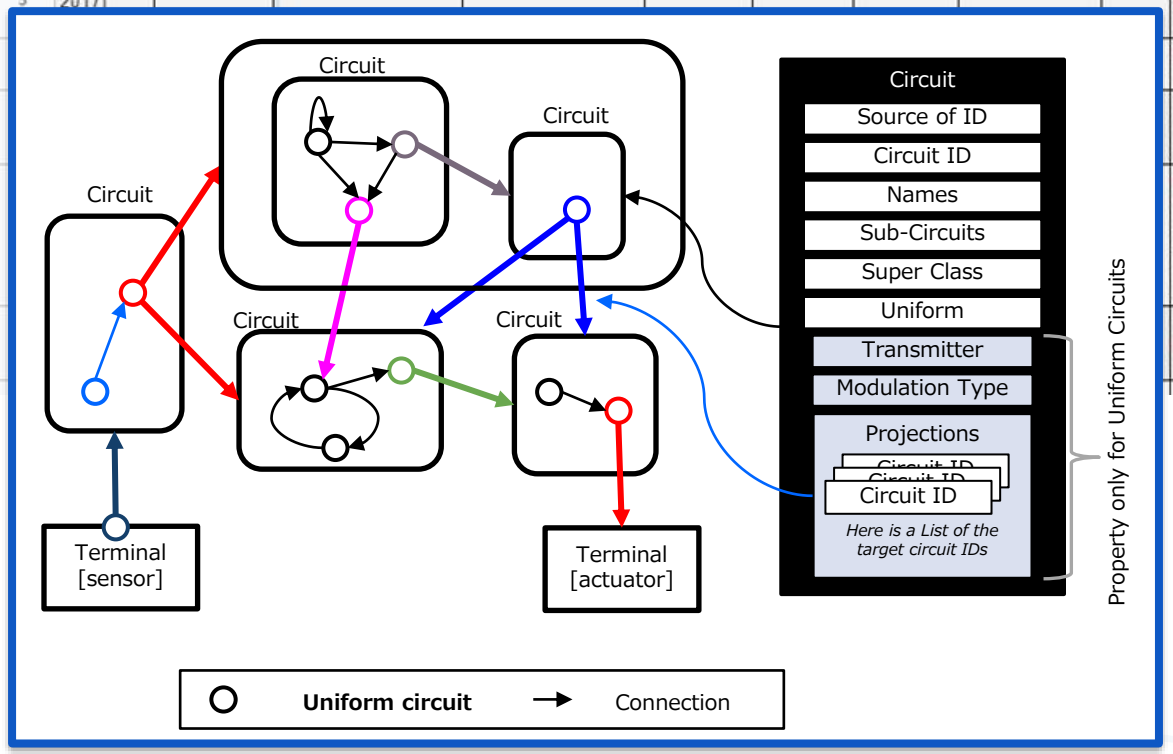


海馬体のBRA形式データ（HF.bra）

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	Source of ID	Circuit ID	Names	Sub-Circuits	Super Class	Uniform	Transmitter	Modulation Type	Size	Projections	Interpretation(φ&f)	Label(1)	Function(1)	Projections in Use(1)
	collection	HPF	Hippocampal	Hipp; LEC; MEC;		FALSE				PERI (origin LEC_deep_uc1);		HPF	Top Level Functions for HPF:	PERI (GIPA:G)
2			formation	CA1; CA3; Fus						Hippo: (origin MEC_deep_uc1);			categorization by integrating allocentric and egocentric information	
3	DHBA	Hipp	Hippocampus											
4	DHBA	CA1	cornu Ammoni							MEC_III [Moser, 2010]; MEC_V [Moser, 2010]; Medial septum [Rolls, 2013]; Nucleus acumens [Rolls, 2013]; PFC.L2 [Verwer, 1997]; PFC.L3 [Verwer, 1997]; S [Llorens-Martín, 2014];	Ensemble activity in CA3, but not in CA1, is sensitive to the content of a scene or place in the environment; CA3 supports the retrieval of memories about where an objects is in a scene [Robertson,1998] [Rolls,1998] or where a reward could be found in the environment [Brun, 2002].			
5	[Bubb, 2017]	CA1_distal	CA1, distal			TRUE		Excitatory		S_proximal [Knierim, 2014]; LEC_deep [Knierim, 2014]; MEC_III [Moser, 2010];	Non-spatial semantic memory [author, year]	C	Place category (internal representation of visual spatial information)	S_proximal (GIPA:G)
										S_distal [Knierim, 2014]; MEC_deep [Knierim, 2014];	Place cells [Brun, 2002] [O'Keefe,1976]	r	Position distribution (cluster information regarding positions)	S_distal (GIPA:G)
										CA1 [Llorens-Martín, 2014]; CA3 [Llorens-Martín, 2014]; MEC_II [Llorens-Martín, 2014];				
										CA1_distal [Knierim, 2015]; CA1_proximal [Knierim, 2015]; CA2 [Llorens-Martín, 2014][Knierim, 2015]; CA3 [Knierim, 2015]; DG [Llorens-Martín, 2014];	Pattern completion, information integration [Kesner, 2007][Rolls, 2007]	H^{III}	Integrated semantic memory and episodic memory of information from X and Z	CA1_distal (GIPA:G)
										CA2 [Llorens-Martín, 2014]; CA3 [Llorens-Martín, 2014]; DG [Knierim, 2015];	Pattern separation [Kesner, 2007][Rolls, 2007]	H^{DG}	Integrated semantic memory	CA3 (GIPA:G)

脳情報フロー
(BIF)

仮説的コンポーネント図
(HCD)



参考資料：

- 脳参照アーキテクチャ(BRA)データの記述マニュアルおよび具体例の公開
- 第1回 WBAレクチャー～認知機能の脳構造に沿った分解手法ー脳機能の体系的理解を目指して

海馬体のHCD形式データ（AT20HippocampalFormation.hcd）

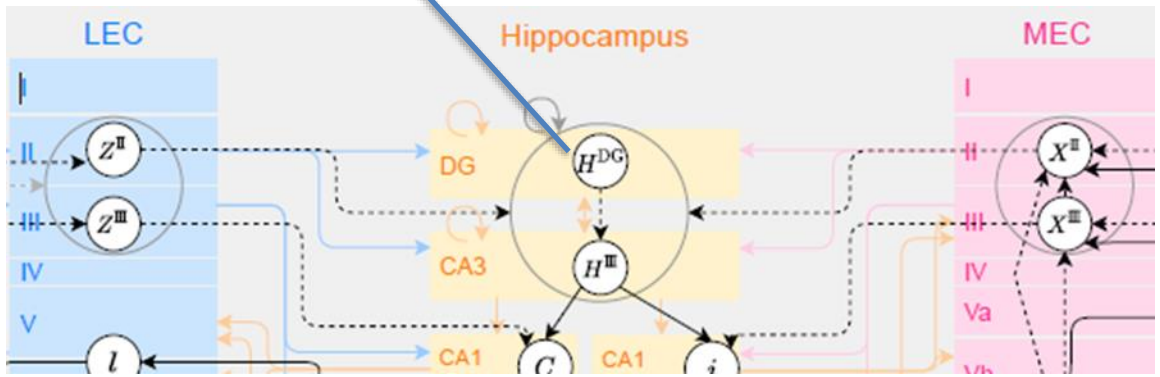
AB	AC	AD	AE	AF	AG	AH	AI	AJ	AK	AL	AM	AN	AO	AP	AQ	AR	AS
Circuit ID	Label (1)	Output Circuits (1)	Output Circuit Validation (1)	Input Circuit (1)	Circuit Summary (1)	Region Category (1)	Process(1)	Output Semantics (1)	Comments (1)	FTV depth (1)	FTV line (1)	Confirmor (1)	Output Semantics Generativity (1)	Process Synthesizability (1)	Confirmed date (1)	Confirmation comments (1)	Confirmation Summary (1)
Hipp	Hipp			-	Hipp (Hipp) -- Input Circuits -- - -- Output Circuits --	inROI	(Composed by sub-process)	Recalled integrated semantic information		1	10	Yuta Ashihara	Probably generatable [W]	Synthesizable	2022/9/18		Confirmation Summary: - Output Semantics is Probably generatable [W] - Process is Synthesizable - Comment :
DG+CA3	H^{DG}			-	DG+CA3 (H^{DG}) -- Input Circuits -- - -- Output Circuits --	inROI	O (DG+CA3) is generated from I(LEC_II)=Z^{II} and I(MEC_II)=X^{II} O=P(H^{DG} | Z^{II}, X^{II})	O (DG+CA3) : Recalled mixed-centric integrated semantic information		2	11	Yuta Ashihara	Generatable	Synthesizable	2022/9/19		Confirmation Summary: - Output Semantics is Generatable - Process is Synthesizable - Comment :
DG	H^{DG}	CA3;	-	LEC_II MEC_II	DG (H^{DG}) [U] -- Input Circuits -- LEC_II MEC_II -- Output Circuits -- CA3;	inROI	O (DG) is generated from I(LEC_II)=Z^{II} and I(MEC_II)=X^{II} O=P(H^{DG} | Z^{II}, X^{II})	O (DG) : Cue information for replaying the integrated semantic memory stored within CA3	(GIPA:G)	3	12	Yuta Ashihara	Generatable	Leaf process w/o synthesis	2022/9/20		Confirmation Summary: - Output Semantics is Generatable - Process is Leaf process w/o synthesis - Comment :
CA3	H^{III}	CA1_distal; CA1_proximal;	- -	DG LEC_II MEC_II	CA3 (H^{III}) [U] -- Input Circuits -- DG LEC_II MEC_II -- Output Circuits -- CA1_distal; CA1_proximal;	inROI	O (CA3) is generated from I(DG)=H^{DG}, I(LEC_II)=Z^{II} and I(MEC_II)=X^{II} O=P(H^{DG} | H^{DG}, ,Z^{II}, X^{II})	O (CA3): Recalled mixed-centric integrated semantic information	(GIPA:G)	3	13	Yuta Ashihara	Generatable	Leaf process w/o synthesis	2022/9/21		Confirmation Summary: - Output Semantics is Generatable - Process is Leaf process w/o synthesis - Comment :
Hipp for LEC				-	Hipp for LEC ( ) -- Input Circuits -- - -- Output Circuits --	inROI	(Composed by sub-process)	Recalled egocentric integrated semantic information (including place-category-related information and visual spatial information))	(GIPA:G)	2	14	Yuta Ashihara	Generatable	Synthesizable	2022/9/22		Confirmation Summary: - Output Semantics is Generatable - Process is Synthesizable - Comment :
CA1_distal	C	S_proximal; LEC_deep_uc1;	- x	CA3 LEC_III	CA1_distal (C) [U] -- Input Circuits -- CA3 LEC_III -- Output Circuits -- S_proximal; LEC_deep_uc1;	inROI	O(CA1_distal) is generated from I(CA3) and I(LEC_III)	O(CA1_distal): Extracted egocentric components of integrated semantic information	(GIPA:G-Δt)	3	15	Yuta Ashihara	Generatable	Leaf process w/o synthesis	2022/9/23		Confirmation Summary: - Output Semantics is Generatable - Process is Leaf process w/o synthesis - Comment :
S_proximal	C'	LEC_deep_uc1;	x	CA1_distal	S_proximal (C') [U] -- Input Circuits -- CA1_distal -- Output Circuits -- LEC_deep_uc1;	inROI	O(S_proximal) is generated from I(CA1_distal)	Stored egocentric components of integrated semantic information (previous time)	(GIPA:G)	3	16	Yuta Ashihara	Generatable	Leaf process w/o synthesis	2022/9/24		Confirmation Summary: - Output Semantics is Generatable - Process is Leaf process w/o synthesis - Comment :
Hipp for MEC				-	Hipp for MEC ( ) -- Input Circuits -- - -- Output Circuits --	inROI	(Composed by sub-process)	Recalled allocentric integrated semantic information (including position-distribution-related information, self-posture information and cluster information regarding positions)		2	17	Yuta Ashihara	Generatable	Synthesizable	2022/9/25		Confirmation Summary: - Output Semantics is Generatable - Process is Synthesizable - Comment :

HCDの機能特性：出力セマンティクス生成性

	D	E	F	G	H	I	J	K
1	Region Category	Depth = 0	Depth = 1	Depth = 2	Depth = 3	Depth = 4	Depth = 5	Depth = 6
2	Input/Output	A35 (y^{A35}) -- Input Circuits -- HIP LEC_deep_uc1 -- Output Circuits --	(Undefined interface process)	Multimodal information related to egocentric self-state aggregated from the neocortex (e.g., proximal distance/landmarks, relative object positions, object category, landscape information)	Confirmation Summary: - Output Semantics is Generatable - Process is Synthesizable - Comment :	-	-	-
3	Input/Output	=====>	A35_uc1 (y^{A35}) [U] -- Input Circuits -- - -- Output Circuits -- LEC_II;	(Undefined interface process)	The prediction part of multimodal egocentric related information for providing to LEC II	Confirmation Summary: - Output Semantics is Generatable - Process is Leaf process w/o synthesis - Comment :	-	-
4	Input/Output	=====>	A35_uc2 (y^{A35}) [U] -- Input Circuits -- - -- Output Circuits -- LEC_III	(Undefined interface process)	The observation part of multimodal egocentric related information for providing to LEC III	Confirmation Summary: - Output Semantics is Generatable - Process is Leaf process w/o synthesis - Comment :	-	-
5	Input/Output	VISpor (y^{POR}) -- Input Circuits -- HIP MEC_deep_uc1 -- Output Circuits --	(Undefined interface process)	Multimodal information related to allocentric self-state aggregated from the neocortex (e.g., distal distance/landmarks, absolute object positions)	Confirmation Summary: - Output Semantics is Generatable - Process is Synthesizable - Comment :	-	-	-
6	Input/Output	=====>	VISpor_uc1 (y^{POR}) [U] -- Input Circuits -- - -- Output Circuits -- MEC_II;	(Undefined interface process)	The prediction part of multimodal allocentric related information for providing to MEC II	Confirmation Summary: - Output Semantics is Generatable - Process is Leaf process w/o synthesis - Comment :	-	-
7	Input/Output	=====>	VISpor_uc2 (y^{POR}) [U] -- Input Circuits -- - -- Output Circuits -- MEC_III;	(Undefined interface process)	The observation part of multimodal allocentric related information for providing to MEC III	Confirmation Summary: - Output Semantics is Generatable - Process is Leaf process w/o synthesis - Comment :	-	-
8	Input	=====>	RSC_uc1 (ω^w) [U] -- Input Circuits -- - -- Output Circuits -- MEC_III;	(Undefined interface process)	Self rotational speed information (related to head direction)	Confirmation Summary: - Output Semantics is Generatable - Process is Leaf process w/o synthesis - Comment :	-	-
9	ROI	HIP (HF) -- Input Circuits -- - -- Output Circuits -- A35; VISpor;	(Composed by sub-process)	Top Level Functions for HF: (i) Self-localization, (ii) Place categorization by integrating allocentric and egocentric information	Confirmation Summary: - Output Semantics is Generatable - Process is Possibly synthesizable [W] - Comment : Output Semanticsの実現性が不明である。	-	-	-
10	inROI	=====>	Hipp (Hipp) -- Input Circuits -- - -- Output Circuits --	(Composed by sub-process)	Recalled integrated semantic information	Confirmation Summary: - Output Semantics is Probably generatable [W] - Process is Synthesizable - Comment :	-	-
11	inROI	-	=====>	DG+CA3 (H^{DG}) -- Input Circuits -- - -- Output Circuits --	O (DG+CA3) is generated from I(LEC_II)=Z^{II} and I(MEC_II)=X^{II}	O (DG+CA3) : Recalled mixed-centric integrated semantic information	Confirmation Summary: - Output Semantics is Generatable - Process is Synthesizable - Comment :	-
12	inROI	-	-	=====>	DG (H^{DG}) [U] -- Input Circuits -- LEC_II MEC_II -- Output Circuits -- CA3;	O (DG) is generated from I(LEC_II)=Z^{II} and I(MEC_II)=X^{II} O=P(H^{DG} | Z^{II}, X^{II})	O (DG) : Cue information for replaying the integrated semantic memory stored within CA3	Confirmation Summary: - Output Semantics is Generatable - Process is Leaf process w/o synthesis - Comment :
13	inROI	-	-	=====>	-- Input Circuits -- DG LEC_II MEC_II -- Output Circuits -- CA1_distal; CA1_proximal;	I(DG)=H^{DG}; I(LEC_II)=Z^{II} and I(MEC_II)=X^{II} O=P(H^{DG} | H^{DG}, Z^{II}, X^{II})	integrated semantic information	- Output Semantics is Generatable - Process is Leaf process w/o synthesis - Comment :
14	inROI	-	=====>	Hipp for LEC ( ) -- Input Circuits -- - -- Output Circuits --	(Composed by sub-process)	Recalled egocentric integrated semantic information (including place-category-related information and visual spatial information))	Confirmation Summary: - Output Semantics is Generatable - Process is Synthesizable - Comment :	-
15	inROI	-	-	=====>	CA1_distal (C) [U] -- Input Circuits -- CA3 LEC_III -- Output Circuits -- S_proximal; LEC_deep_uc1;	O(CA1_distal) is generated from I(CA3) and I(LEC_III)	O(CA1_distal): Extracted egocentric components of integrated semantic information	Confirmation Summary: - Output Semantics is Generatable - Process is Leaf process w/o synthesis - Comment :
16	inROI	-	-	=====>	S_proximal (C') [U] -- Input Circuits -- CA1_distal -- Output Circuits -- LEC_deep_uc1;	O(S_proximal) is generated from I(CA1_distal)	Stored egocentric components of integrated semantic information (previous time)	Confirmation Summary: - Output Semantics is Generatable - Process is Leaf process w/o synthesis - Comment :
	inROI	-	=====>	Hipp for MEC ( )	(Composed by sub-process)	Recalled allocentric integrated	Confirmation Summary:	-

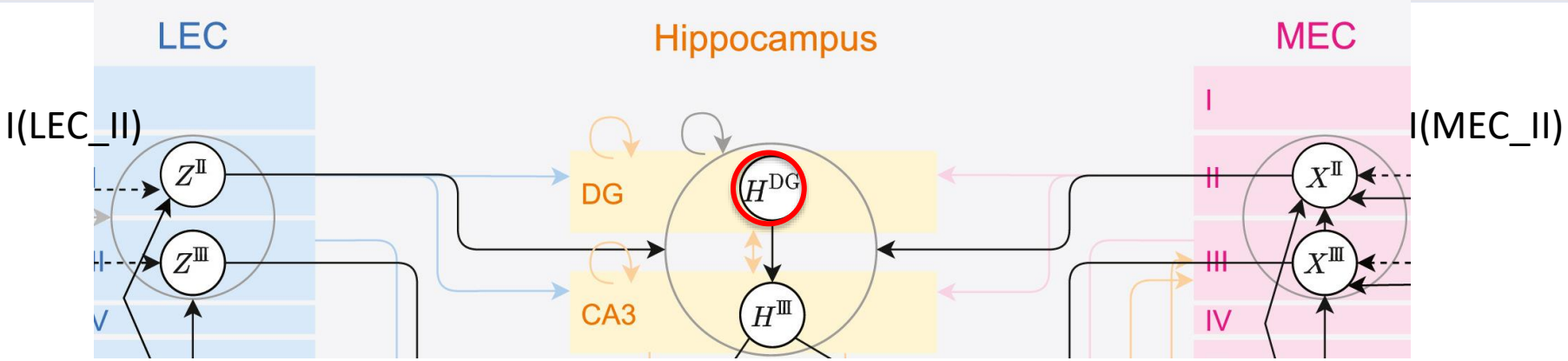
出力セマンティクス生成性：
このコンポーネントのOutput Semanticsが、指定された回路からの入力を使用するこのコンポーネントのProcessによって生成しうるか否かを評価

Summary	Process	Output Semantics
DG (H^{DG}) [U] -- Input Circuits -- LEC_II MEC_II -- Output Circuits -- CA3;	O (DG) is generated from I(LEC_II)=Z^{II} and I(MEC_II)=X^{II} O=P(H^{DG} | Z^{II}, X^{II})	O (DG) : Cue information for replaying the integrated semantic memory stored within CA3



図：海馬体のFunction Tree Viewerの一部

確率的生成モデルによるHCDにおけるプロセス記述



$$O = P(H^{DG} | Z^{II}, X^{II})$$

Circuit ID、ラベル入力、出力

Process

DG (H^{DG}) [U] -- Input Circuits -- LEC_II MEC_II -- Output Circuits -- CA3;	O (DG) is generated from I(LEC_II)=Z^{II} and I(MEC_II)=X^{II} O=P(H^{DG} | Z^{II}, X^{II})	O (DG) : Cue information for replaying the integrated semantic memory stored within CA3
CA3 (H^{III}) [U]	O (CA3) is generated from	O (CA3): Recalled mixed contric

Output Semantics

HCDの機能特性：プロセス合成性

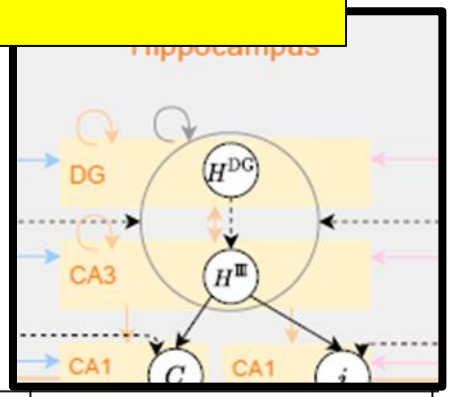
	D	E	F	G	H	I	J	K
1	Region Category	Depth = 0	Depth = 1	Depth = 2	Depth = 3	Depth = 4	Depth = 5	Depth = 6
2	Input/Output	A35 (y^{A35}) -- Input Circuits -- HIP LEC_deep_uc1 -- Output Circuits --	(Undefined interface process)	Multimodal information related to egocentric self-state aggregated from the neocortex (e.g., proximal distance/landmarks, relative object positions, object category, landscape information)	Confirmation Summary: - Output Semantics is Generatable - Process is Synthesizable - Comment :	-	-	-
3	Input/Output	=====>	A35_uc1 (y^{A35}) [U] -- Input Circuits -- - -- Output Circuits -- LEC_II;	(Undefined interface process)	The prediction part of multimodal egocentric related information for providing to LEC II	Confirmation Summary: - Output Semantics is Generatable - Process is Leaf process w/o synthesis - Comment :	-	-
4	Input/Output	=====>	A35_uc2 (y^{A35}) [U] -- Input Circuits -- - -- Output Circuits -- LEC_III	(Undefined interface process)	The observation part of multimodal egocentric related information for providing to LEC III	Confirmation Summary: - Output Semantics is Generatable - Process is Leaf process w/o synthesis - Comment :	-	-
5	Input/Output	VISpor (y^{POR}) -- Input Circuits -- HIP MEC_deep_uc1 -- Output Circuits --	(Undefined interface process)	Multimodal information related to allocentric self-state aggregated from the neocortex (e.g., distal distance/landmarks, absolute object positions)	Confirmation Summary: - Output Semantics is Generatable - Process is Synthesizable - Comment :	-	-	-
6	Input/Output	=====>	VISpor_uc1 (y^{POR}) [U] -- Input Circuits -- - -- Output Circuits -- MEC_II;	(Undefined interface process)	The prediction part of multimodal allocentric related information for providing to MEC II	Confirmation Summary: - Output Semantics is Generatable - Process is Leaf process w/o synthesis - Comment :	-	-
7	Input/Output	=====>	VISpor_uc2 (y^{POR}) [U] -- Input Circuits -- - -- Output Circuits -- MEC_III;	(Undefined interface process)	The observation part of multimodal allocentric related information for providing to MEC III	Confirmation Summary: - Output Semantics is Generatable - Process is Leaf process w/o synthesis - Comment :	-	-
8	Input	=====>	RSC_uc1 (ω^w) [U] -- Input Circuits -- - -- Output Circuits -- MEC_III;	(Undefined interface process)	Self rotational speed information (related to head direction)	Confirmation Summary: - Output Semantics is Generatable - Process is Leaf process w/o synthesis - Comment :	-	-
9	ROI	HIP (HF) -- Input Circuits -- - -- Output Circuits -- A35; VISpor;	(Composed by sub-process)	Top Level Functions for HF: (i) Self-localization, (ii) Place categorization by integrating allocentric and egocentric information	Confirmation Summary: - Output Semantics is Generatable - Process is Possibly synthesizable [W] - Comment : Output Semanticsの実現性が不明である。	-	-	-
10	inROI	=====>	Hipp (Hipp) -- Input Circuits -- - -- Output Circuits --	(Composed by sub-process)	Recalled integrated semantic information	Confirmation Summary: - Output Semantics is Probably generatable [W] - Process is Synthesizable - Comment :	-	-
11	inROI	-	=====>	DG+CA3 (H^{DG}) -- Input Circuits -- - -- Output Circuits --	O (DG+CA3) is generated from I(LEC_II)=Z^{II} and I(MEC_II)=X^{II} O=P(H^{DG} | Z^{II}, X^{II})	O (DG+CA3) : Recalled mixed-centric integrated semantic information	Confirmation Summary: - Output Semantics is Generatable - Process is Synthesizable - Comment :	-
12	inROI	-	-	=====>	DG (H^{DG}) [U] -- Input Circuits -- LEC_II MEC_II -- Output Circuits -- CA3;	O (DG) is generated from I(LEC_II)=Z^{II} and I(MEC_II)=X^{II} O=P(H^{DG} | Z^{II}, X^{II})	O (DG) : Cue information for replaying the integrated semantic memory stored within CA3	Confirmation Summary: - Output Semantics is Generatable - Process is Leaf process w/o synthesis - Comment :
13	inROI	-	-	=====>	CA3 (H^{III}) [U] -- Input Circuits -- DG LEC_II MEC_II -- Output Circuits -- CA1_distal; CA1_proximal;	O (CA3) is generated from I(DG)=H^{DG}, I(LEC_II)=Z^{II} and I(MEC_II)=X^{II} O=P(H^{DG} | H^{DG}, ,Z^{II}, X^{II})	O (CA3): Recalled mixed-centric integrated semantic information	Confirmation Summary: - Output Semantics is Generatable - Process is Leaf process w/o synthesis - Comment :
14	inROI	-	=====>	Hipp for LEC ( ) -- Input Circuits -- - -- Output Circuits --	(Composed by sub-process)	Recalled egocentric integrated semantic information (including [illegible] and visual spatial information))	Confirmation Summary: - Output Semantics is Generatable - Process is Synthesizable - Comment :	-
15	inROI	-	-	=====>	CA1_distal (C) [U] -- Input Circuits -- CA3 LEC_III -- Output Circuits -- S_proximal; LEC_deep_uc1;	O(CA1_distal) is generated from I(CA3) and I(LEC_III)	O(CA1_distal): Extracted egocentric components of integrated semantic information	Confirmation Summary: - Output Semantics is Generatable - Process is Leaf process w/o synthesis - Comment :
16	inROI	-	-	=====>	S_proximal (C') [U] -- Input Circuits -- CA1_distal -- Output Circuits -- LEC_deep_uc1;	O(S_proximal) is generated from I(CA1_distal)	Stored egocentric components of integrated semantic information (previous time)	Confirmation Summary: - Output Semantics is Generatable - Process is Leaf process w/o synthesis - Comment :
	inROI	-	=====>	Hipp for MEC ( )	(Composed by sub-process)	Recalled allocentric integrated	Confirmation Summary:	-

図：海馬体のFunction Tree Viewerの一部

プロセス合成性：
このコンポーネントに記述されたプロセスが、下位のコンポーネントのプロセスを合成することによって実現できるか否かを評価

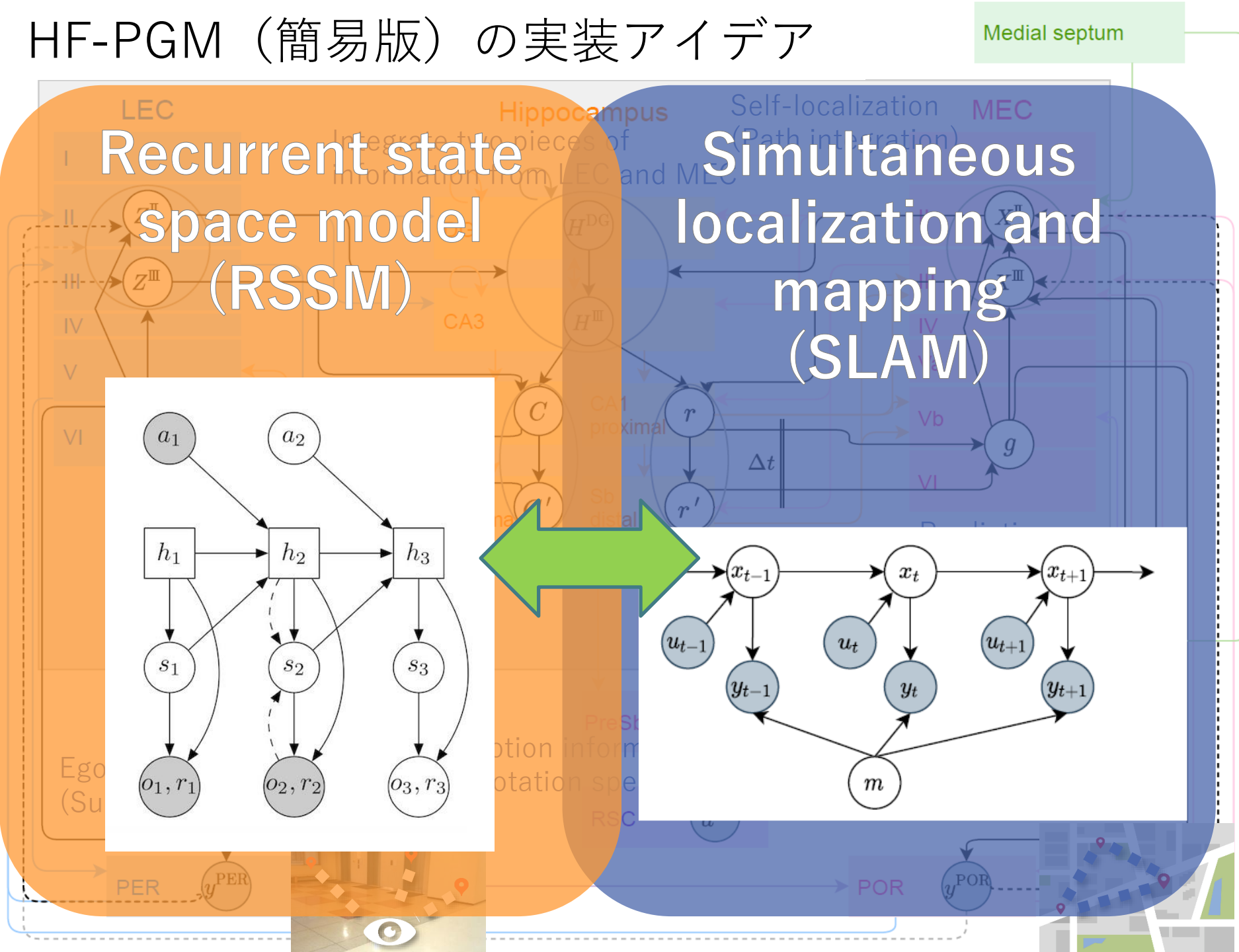
H^{DG}とH^{III}の同時分布として書ける

ss Aは、
H^{III}の合成
を評価する



DG+CA3 ( ) -- Input Circuits -- - -- Output Circuits --	O (DG+CA3) is generated from I(LEC_II)=Z^{II} and I(MEC_II)=X^{II} H^{DG}, O=P(H^{III} | Z^{II}, X^{II}) Process A	O (DG+CA3) : Recalled mixed-centric integrated semantic information
=====>	DG (H^{DG}) [U] -- Input Circuits -- LEC_II MEC_II -- Output Circuits -- CA3;	O (DG) is generated from I(LEC_II)=Z^{II} and I(MEC_II)=X^{II} Process H^{DG} O=P(H^{DG} | Z^{II}, X^{II})
=====>	CA3 (H^{III}) [U] -- Input Circuits -- DG LEC_II MEC_II -- Output Circuits -- CA1_distal; CA1_proximal;	O (CA3) is generated from I(DG)=H^{DG}, I(LEC_II)=Z^{II} and I(MEC_II)=X^{II} O=P(H^{ III } | H^{DG}, ,Z^{II}, X^{II}) Process H^{III}

HF-PGM（簡易版）の実装アイデア



Symbol	Function of components on HCD
C	Place category (internal representation of visual spatial information)
r	Position distribution (cluster information regarding positions)
C'	Place category at the previous time
r'	Position distribution at the previous time
H^{III}	Integrated semantic memory and episodic memory of information from X and Z
H^{DG}	Integrated semantic memory
X^{II} ($\{x_t\}$)	Self-position information, predictive distribution
X^{III} ($\{x_t\}$)	Self-posture information (position and orientation), observation likelihood
g	Predictive representation of X (Prediction at future time regarding movement/speed amount or posture)
Z^{II}	Abstraction of information from y^{PER} (transmission of prediction, generation of prediction signal)
Z^{III}	Abstraction of information from y^{PER} (Observation transmission)
l	Predictive representation of Z (Prediction at future time from the difference between C' and C)
X' ($\{x_{t-1}\}$)	Self-posture information
y^{POR} ($\{y_t\}$)	Allocentric visual information (distal distance/landmarks, absolute object positions)
y^{PER}	Egocentric visual information (proximal distance/landmarks, relative object positions, object category, landscape information)
u^w ($\{u_t\}$)	Rotational speed movement

まとめ

- 空間認知の機能を担う**SLAMと海馬体の知見の橋渡し**を目指した
- PGMベースのSLAMと海馬体の脳科学的知見をまとめ、それらの関連性を調査・議論した
- **海馬体の機能や解剖学的構造と整合性のとれたPGM**を構築した
  - 布川らが提案した海馬体のBIFをベースにLECを加えたBIFに発展させ議論
  - PGMベースのSLAMやSpCoSLAMを海馬体BIFの解剖学的構造に合うように拡張
- HF-PGMの従来のSLAMとの主な違い
  - MECのみならずLECも統合してモデル化

- 今後の方向性
  - HF-PGMをWB-PGMのサブモジュールとして統合
  - 生成モデル・推論モデルの確率分布やアーキテクチャの詳細設定
  - 移動ロボットへの実装・導入

Brain-inspired probabilistic generative model for double articulation analysis of spoken language

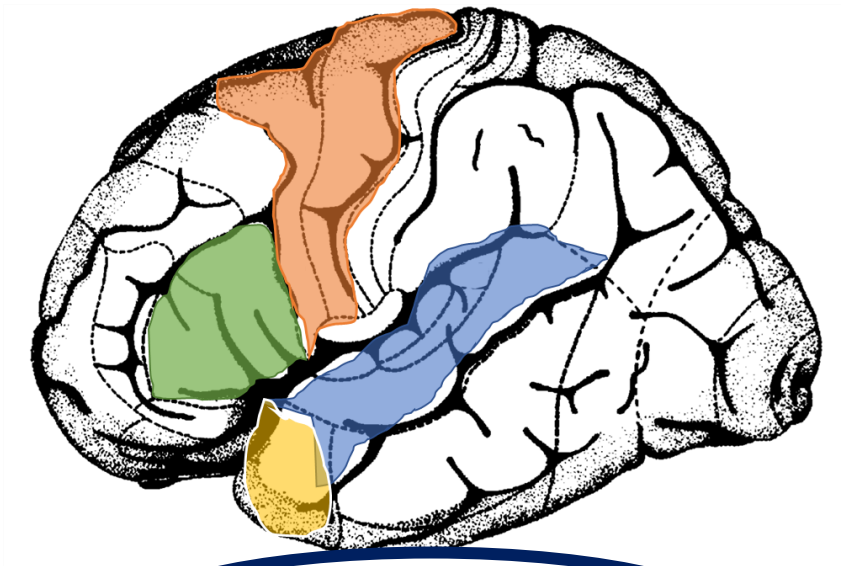
音声言語の二重分節解析を担う脳参照アーキテクチャの設計

室 茉央子　(立命館大)
谷口 彰　(立命館大)
山川 宏　(WBAI/東大/理研)
谷口 忠大　(立命館大)

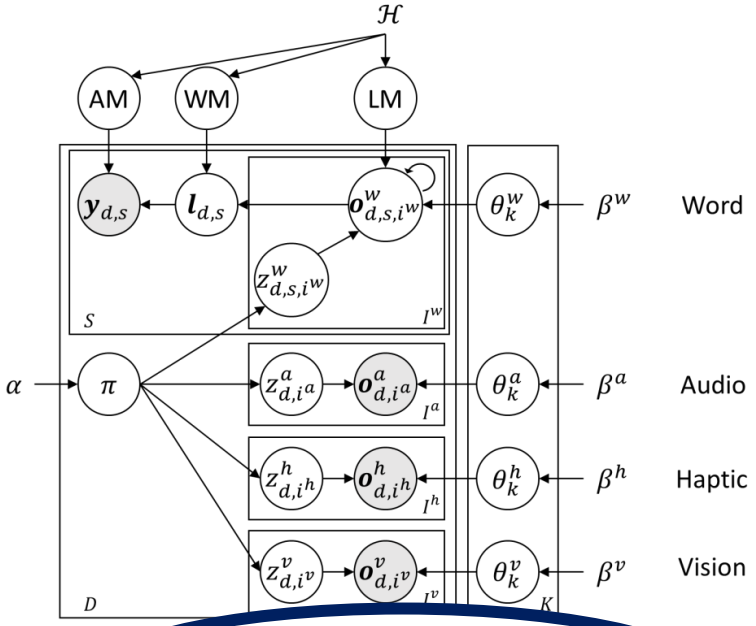
Akira Taniguchi, Maoko Muro, Hiroshi Yamakawa, Tadahiro Taniguchi, "Brain-inspired probabilistic generative model for double articulation analysis of spoken language“, IEEE International Conference on Development and Learning, 2022.

研究目的

脳参照アーキテクチャ開発のアプローチに基づいて
脳内の二重分節解析の構造や機能について調査し,
既存の機械学習手法を参考にしつつ,
整合性のとれた**確率的生成グラフィカルモデルを構築する**



脳内音声言語処理
の知見

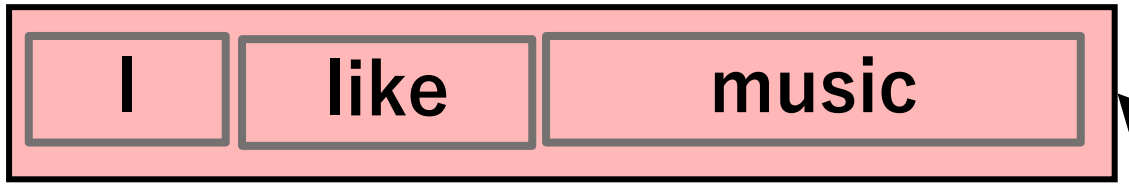


既存の計算機の
確率的生成モデル

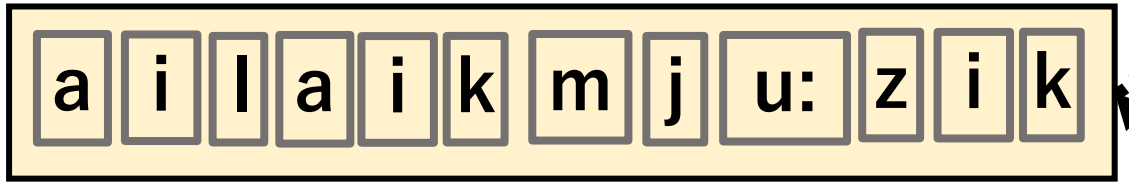
NPB-DAA：Nonparametric Bayesian Double Articulation Analyzer [3]

- 音声の音響特徴量から発話中の音素・単語を発見

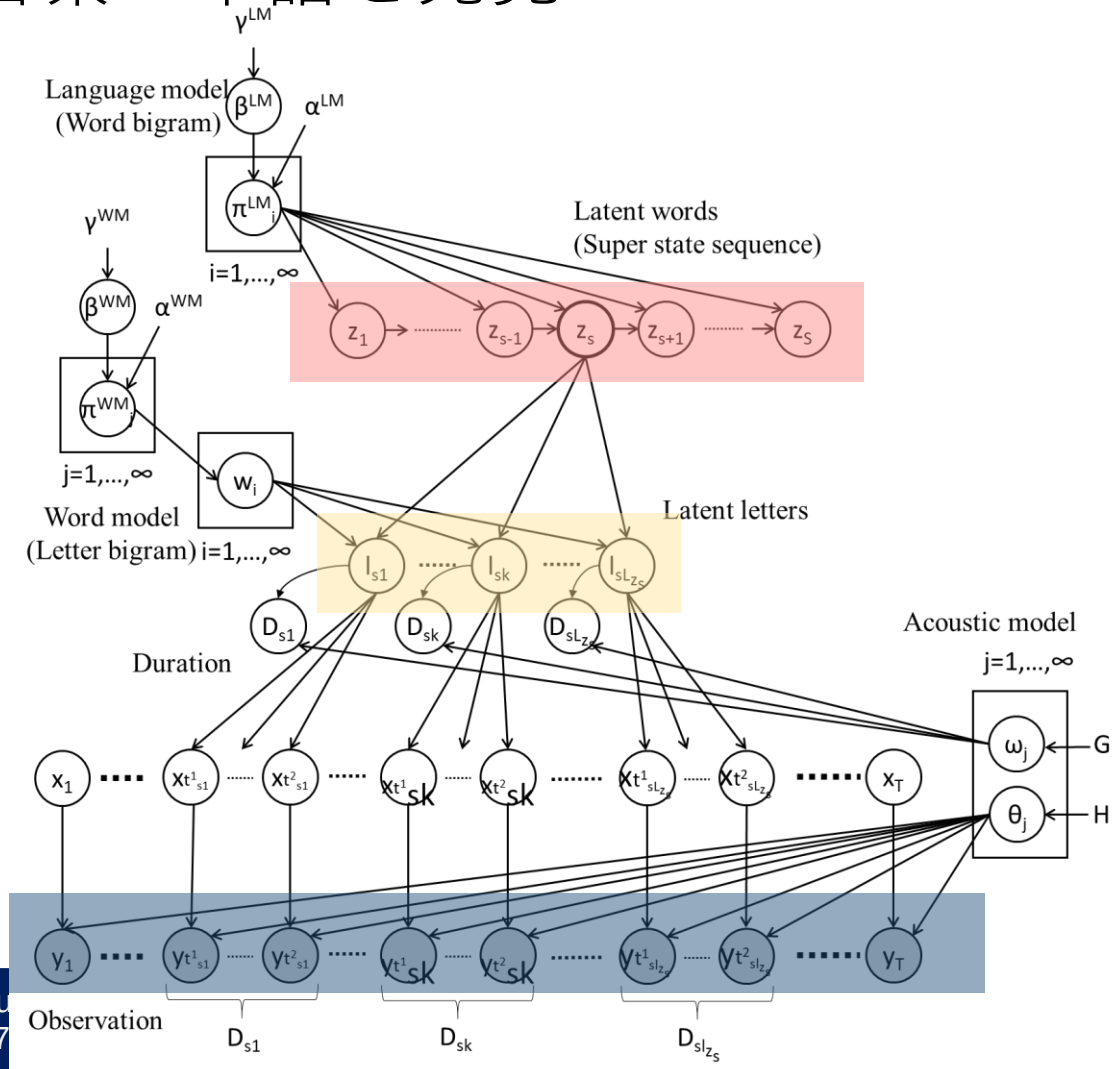
単語列



音素列



音声信号



[3]Taniguchi, Tadahiro, Shogo Nagasaka, and Ryo Nakashima. "Nonparametric bayesian dou
speech signals." *IEEE Transactions on Cognitive and Developmental Systems* 8.3 (2016): 17

Previous study: Extended NPB-DAA

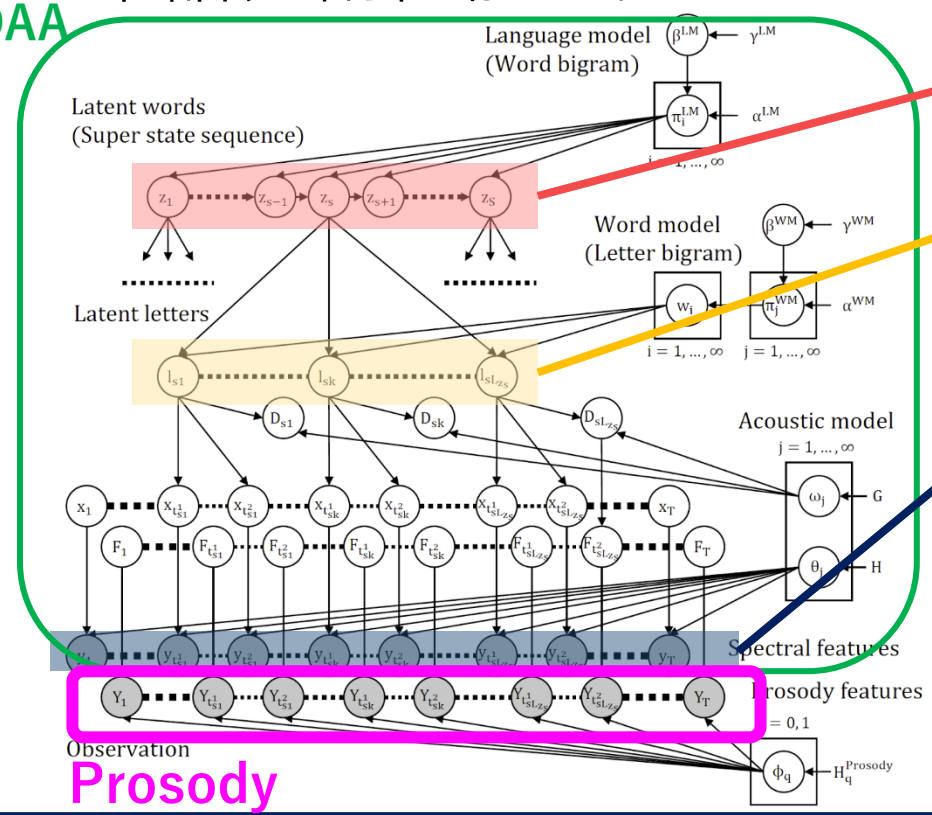
ProsodicDAA[4]

- プロソディの付与することで単語分割性能が向上

NPB-DAA + MLDA[2]

- 聴覚・視覚・触覚情報の統合から単語分割性能が向上

NPBDAA

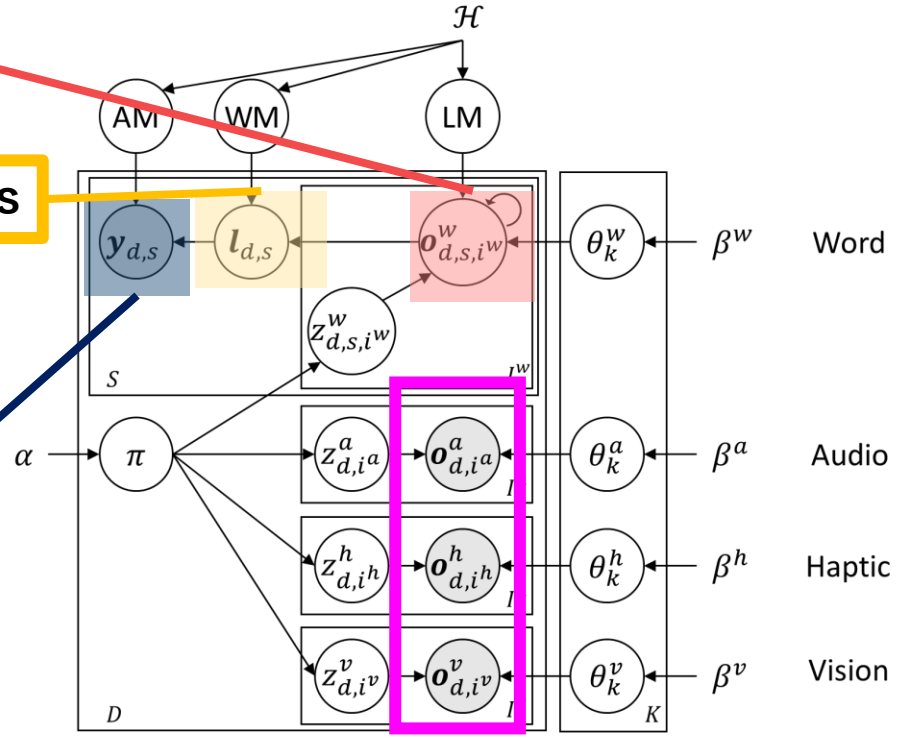


Prosody

Words

Phonemes

speech



Co-occurrence cues

[4]Okuda, Yasuaki, Ryo Ozaki, and Tadahiro Taniguchi. "Double Articulation Analyzer with Prosody for Unsupervised Word and Phoneme Discovery." *arXiv preprint arXiv:2103.08199* (2021).

NPB-DAAを応用した音声言語獲得手法

ProsodicDAA[4]

- プロソディの付与することで単語分割性能が向上

NPB-DAA + MLDA[2]

- 聴覚・視覚・触覚情報の統合から単語分割性能が向上

NPBDAA

単語列

問題点

ヒトの脳を参考にして作られていない

➢ ヒトの脳内の構造や処理の過程と

一致しているかどうか検証されていない

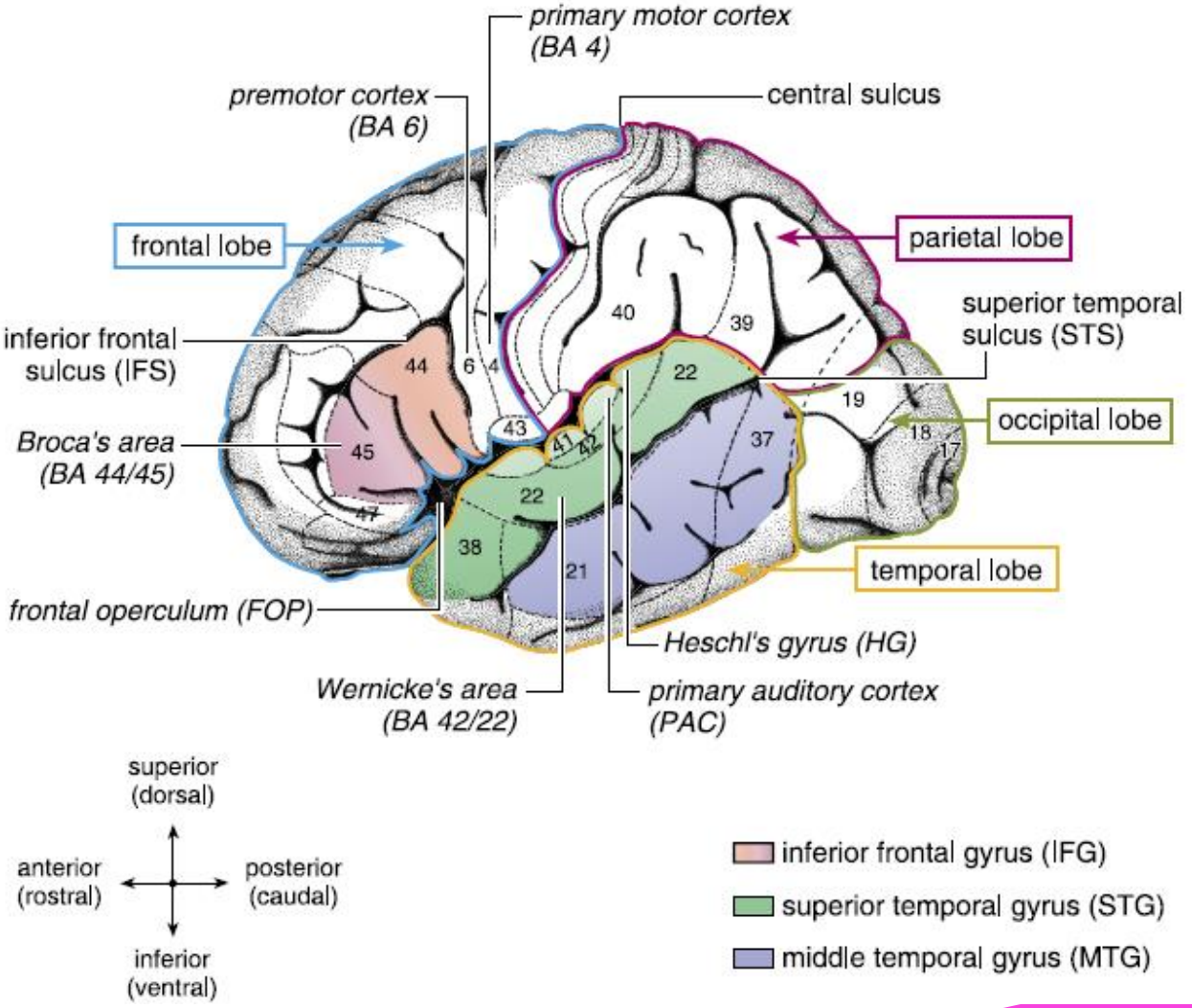
プロソディ

共起情報

[4]Okuda, Yasuaki, Ryo Ozaki, and Tadahiro Taniguchi. "Double Articulation Analyzer with Prosody for Unsupervised Word and Phoneme Discovery." *arXiv preprint arXiv:2103.08199* (2021).

調査内容 -音声言語に関わる領域- [6-16]

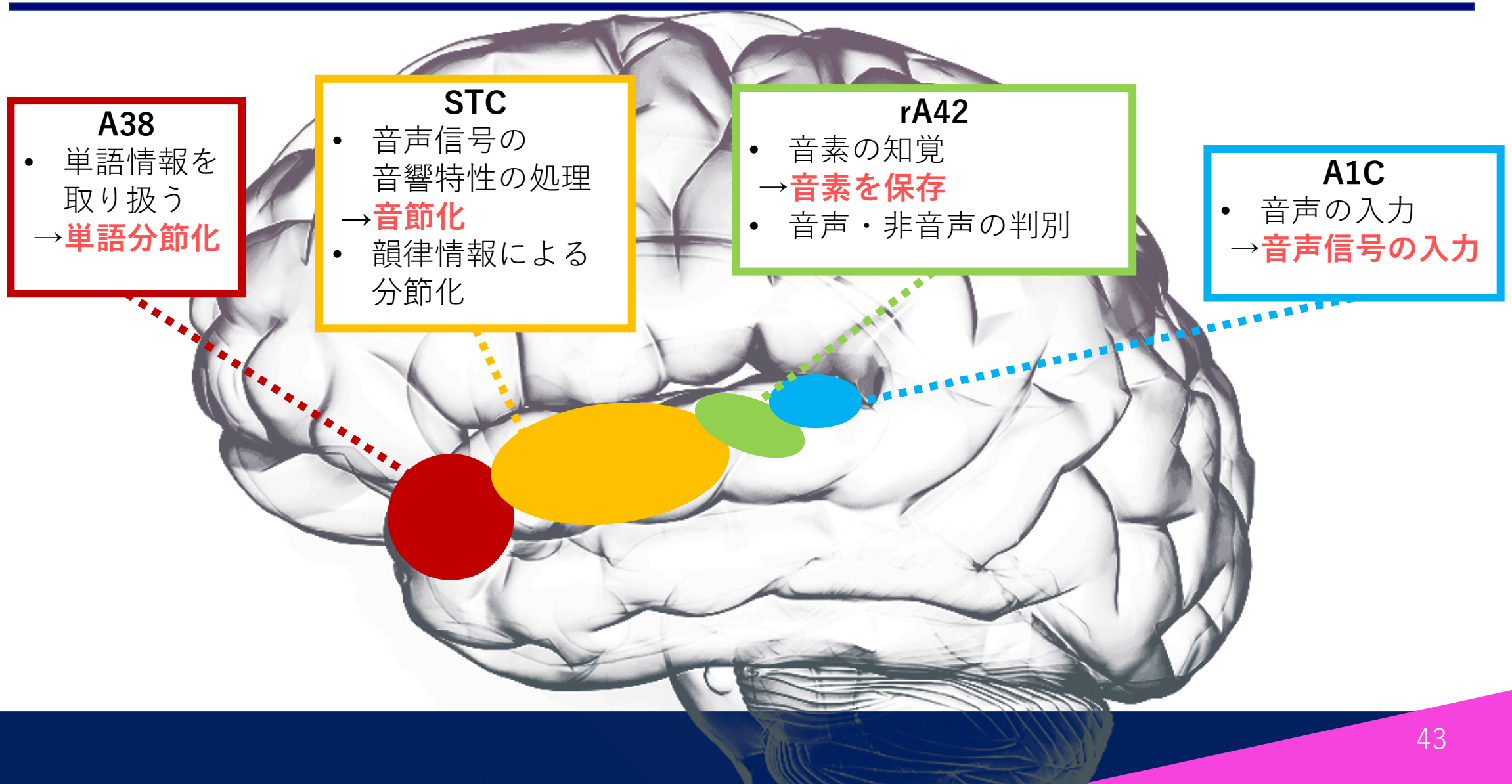
- 一次聴覚野(A1C)：
  音声信号の入力,
  スペクトルの時系列分析と
  音韻的分析
- 二次聴覚野(rA42)：
  音素の知覚,
  音声・非音声の判別
- ブロードマンエリア22(A22)：
  音声信号の音響特性の処理,
  音韻貯蔵・音韻表象の形成
- ブロードマンエリア38(A38)：
  単語情報を扱う,
  モダリティの意味情報のハブ



二重分節解析に関わりそうな文献一覧 [6-16]

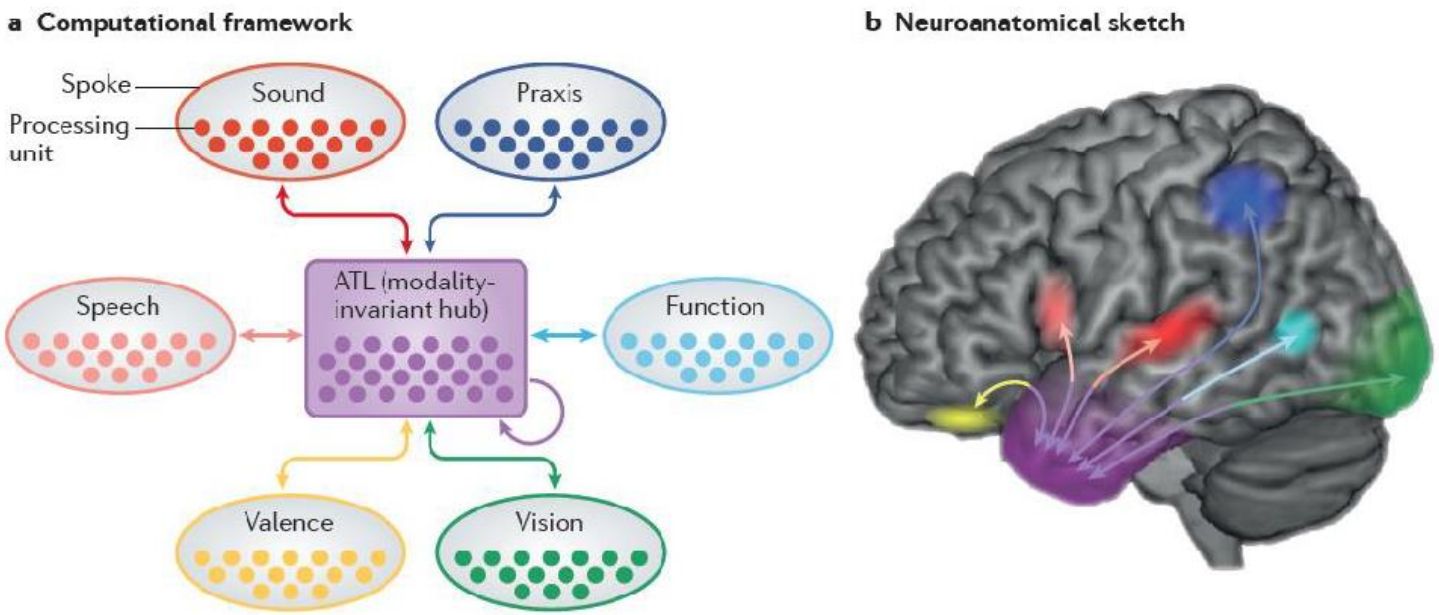
Reference ID	Authors	Type	Title	DOI
Chang, 2015	Chang, E. F., Raygor, K. P., & Berger, M. S.	Article	Contemporary model of language organization: an overview for neurosurgeons.	10.3171/2014.10.JNS132647
Marslen-Wilson, 2007	Marslen-Wilson, W. D., & Tyler, L. K.	Article	Morphology, language and the brain: the decompositional substrate for language comprehension.	10.1098/rstb.2007.2091
Cognition, 2004	P. Indefrey, W.J.M. Levelt	Article	The spatial and temporal signatures of word production components	
Front. Neurosci., 27 March 2018	Francisco Aboitiz	Article	A Brain for Speech. Evolutionary Continuity in Primate and Human Auditory-Vocal Processing	10.3389/fnins.2018.00174
Brain Sci. 2018	Tatsuya Daikoku	Article	Neurophysiological Markers of Statistical Learning in Music and Language: Hierarchy, Entropy and Uncertainty	10.3390/brainsci8060114
Friederici, 2011	Friederici, A. D.		The brain basis of language processing: from structure to function. Physiological Reviews, 91(4), 1357–1392.	10.1152/physrev.00006.2011
Ralph, 2017	Matthew A. Lambon Ralph, Elizabeth Jefferies, Karalyn Patterson & Timothy T. Rogers	Article	The neural and computational bases of semantic cognition	
Fridriksson, 2018	Fridriksson, J., den Ouden, D.-B., Hillis, A. E., Hickok, G., Rorden, C., Basilakos, A., Yourganov, G., & Bonilha, L. (2018).	Article	Anatomy of aphasia revisited. Brain: A Journal of Neurology, 141(3), 848–862.	10.1093/brain/awx363
J. Neurosci., March 6, 2013	Michael F. Bonner1 and Amy R. Price	Article	Where Is the Anterior Temporal Lobe and What Does It Do?	
Gupta2020	Anu Gupta, MV Padma Srivastava	Article	Newer Paradigms in Language Neurobiology	10.4103/aian.AIAN_487_20
Bajada2015	Claude J. Bajada, Matthew	Article	Transport for language south of the Sylvian fissure: The routes and history of the main tracts and stations in the ventral language network	

二重分節解析機能に関係する領域と対応する機能

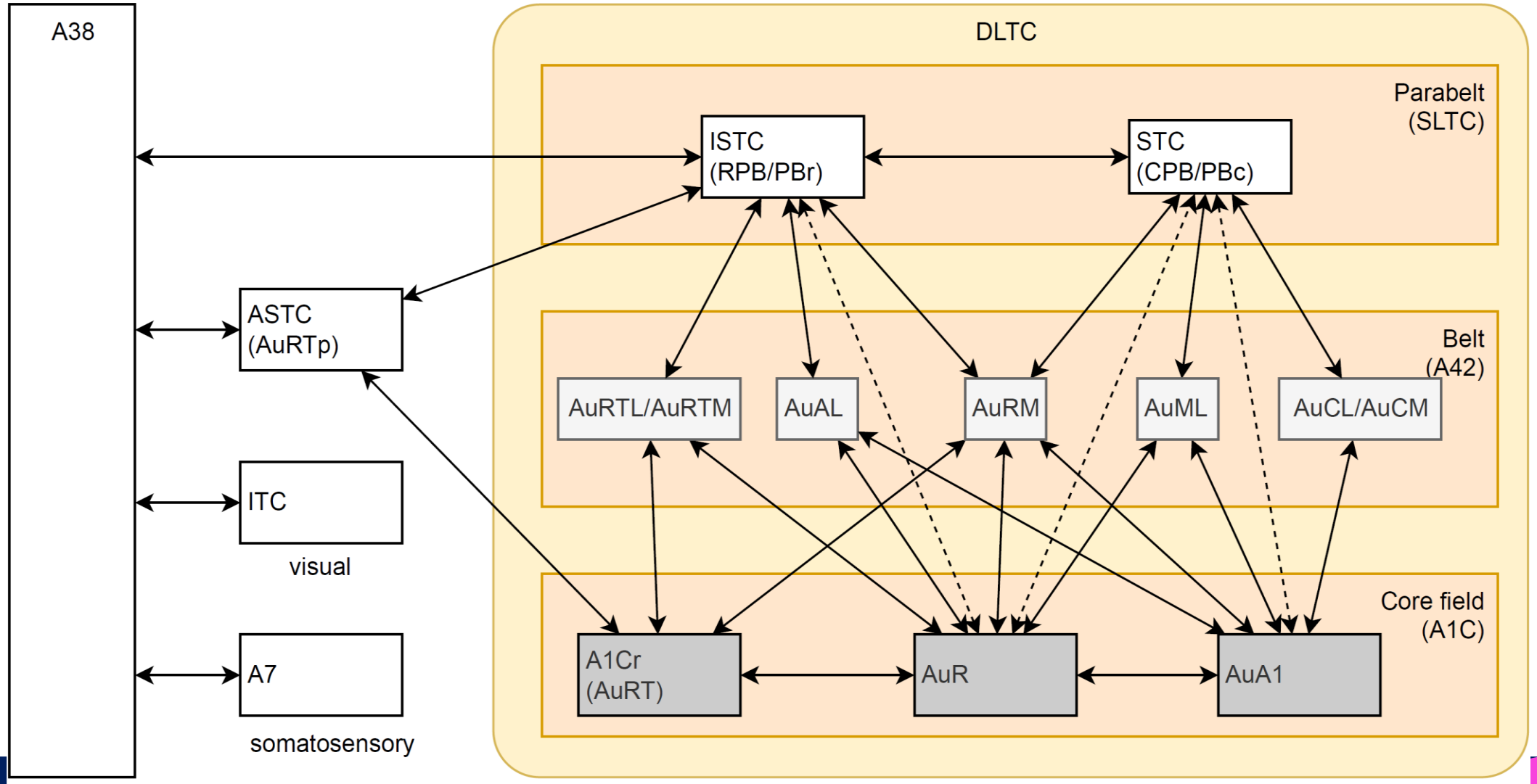


モダリティの意味情報のハブ [6-16]

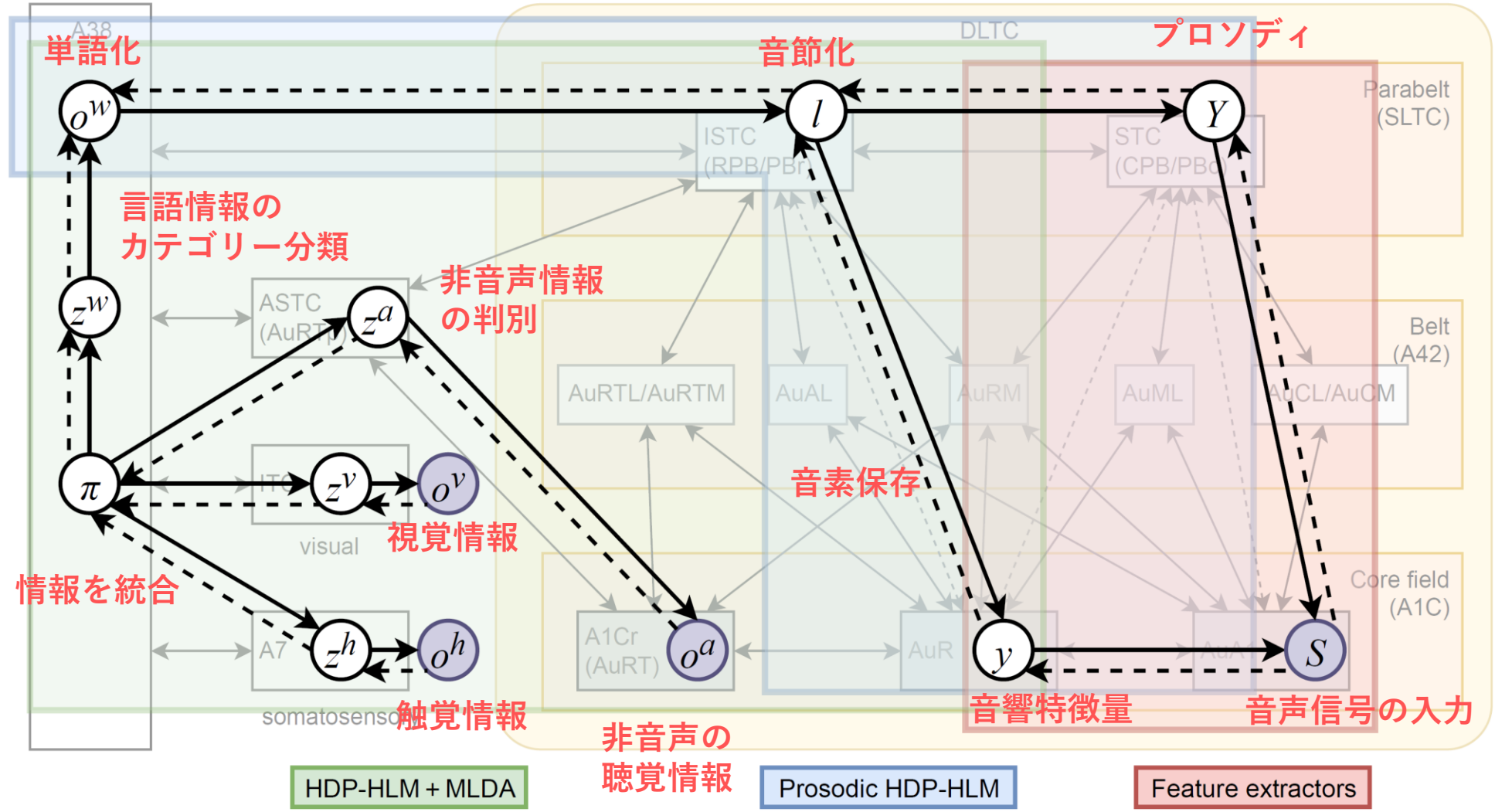
- **ハブ＆スポークモデル**：
  言語および非言語的な経験による
  概念を構築するための中核的な材料（material）となり、
  これらの情報源は**脳全体に分布している特異的な皮質（＝スポーク）に対応していると仮定したモデル**
- 全モダリティ固有な情報源のクロスモーダルな相互作用は、
  the anterior temporal lobes（ATLs）の両側に位置する単一のトランスモーダルハブによって媒介されると提唱している

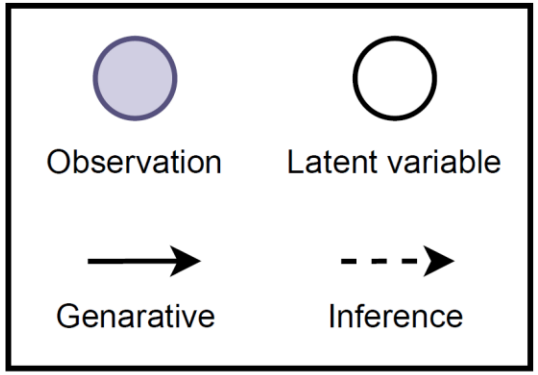


Brain information flow (BIF)



BIFの上に配置した
音声言語の二重分節解析のグラフィカルモデル





まとめ・今後の展望

まとめ

- 脳の解剖学的知見から**二重分節解析の脳情報フロー図を設計**
- 設計した図から二重分節解析機能の関心脳領域と機能を設定し仮説を立てた
- 立てた仮説から確率的生成モデルを構築し，既存モデルとの**変数の表現や確率分布の機能の一致を確認できた**

今後の展望

- 音声の二重分節解析モデルの実装
- 提案したグラフィカルモデルにおいて捉えられていない範囲におけるモデルの拡張

後継者・共同研究者 募集

- HF-PGM・音声言語の二重分節のPGMの**実装・導入**など、Brain-inspired PGMやWB-PGMの取り組み**や共同研究**に興味・関心のある方は、お気軽にお声がけください。
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ご清聴ありがとうございました

本研究にあたっては、
新学術領域研究「人工知能と脳科学の対照と融合」
新学術領域研究「脳情報動態を規定する多領野連関と並列処理」
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