# Libgirl Team Technological Work Collections

Libgirl Team
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## Purpose of This Document

Making artificial general intelligence (AGI) is the technological goal of the Libgirl team. Whichever high-tech firm or government lab succeed in inventing the first AGI will obtain a potentially world-dominating technology. (Naudé & Dimitri, 2019)
This document provides materials to support that we are the champion team to achieve AGI.

## Abstract

We are the only team in the world already drew the whole roadmap about how to make AGI and have been executing it. Since team establishment in May 2018, Libgirl team has been doing all things from AI philosophy, psychology, mathematics, neuroscience, product development, to entrepreneurship. Adaptively following our AGI blueprint, we

Made

1. *Toward Human-Like AI* report, a blueprint to achieve human level AGI, based on Wittgenstein philosophy and developmental psychology.
2. *Principles of Intelligence - Outline Draft*, our systematic knowledge which links and explains all concepts from intelligence, consciousness, emotion, learning, symbol, rationality, ego, thinking, decision making, semantics, understanding, originality, depression, to wisdom.
3. General supervised learning/reinforcement learning algorithm for spiking neural network.
4. WheatNNLeak, a spiking neural network development framework built in Rust programming language.
5. Dong, a machine learning operation (MLOps) platform. It's a Rails plus Heroku analogy for machine learning.
6. Donut, an on-premise MLOps tool. It's a machine learning model management software designed with Domain Driven Design (DDD) methodology.
7. Libgirl Bot, a B2C cloud AI. The public alpha version, serving real users, is an Instant Messenging ChatBot with not only emotional support, small talk, but also product recommendation features.

Developing and will submit for patents

1. Inner Voice, an AI technology making the machine capable of thinking and reasoning, Seeing the demonstration, the public will agree the machine has a mind and it can think.
2. Hebbian Digraph, a neural network designed for self-supervised learning. It will revolutionize gradient descent dominated AI industries.

In the progress of publishing on the Internet

- *Making Real AI* series, a slides series transcribed from *Principles of Intelligence - Outline Draft.* It is introducing one concept a time clearly in each deck of slides in order to persuade the knowledgeable public that we know the most about how to make AGI.

With such global level distinct momentum in a team never riching 5 fulltime R&D manpower yet continuing to grow (let part time half manpower), Libgirl can, in highly potential, be the first team to realize AGI.

# Core Assumption

Our core assumption is that the first team to achieve AGI should have top cross domain knowledge integration ability with exceptional execution speed like entrepreneurs, for the sole reason that

1. What intelligence is, essentially a philosophical problem, has to be clarified.
2. The answer from philosohpy has to be integrated with psychology.
3. The relationship between psychology and neuroscience has to be established.
4. Part of such neuroscience should be formalized as algorithm design.
5. Algorithm design should consider actual implementation.
6. The actual implementation should meet the right user experience as an AGI product. For intelligence itself is quite a concept of application.
7. The team has to understand world economics to glimpse the collective wish for the AGI development.

# Problems

We live in an era unfriendly to generality formulation, which indirectly slowed the development of AGI. Human knowledge is further and further divided into individual domains (specialist) instead of becoming fewer number of integrated knowledge systems. (generalist) “The inevitable outcome is scientific separatism and specialist mythology, which spells death to universality.” (Jung, 1921/2017, p. 261)

# Our Team is the Solution

1. We drew a full picture at the beginning which guides us.
   That is *Toward Human-Like AI* and *Principles of Intelligence.*
2. We do everything mentioned in the core assumption.
3. We are hackers and entrepreneurs. We code and make products instead of laboratory work.
4. All above supports that we are generalists, which is perfect for making AGI.

# Connecting all our works

With *Toward Human-Like AI* report and *Principles of Intelligence,* we know the roadmap to build AGI.
With SNN research and WheatNNLeak open source project, we're prepared to take advantage of the 3rd generation of artificial neural networks (Maass, 1997) when the time is ready.
We stopped the Dong project, but kept Donut as our internal used MLOps tool.
We're developing Inner Voice as machine thinking and reasoning technology. Along with Hebbian Digraph, we'll test them in Libgirl Bot.

# Sum up

Projecting our development progress into the future, we'll achieve AGI.
Join our journey. It is one of humans' greatest ventures.

# Reference


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# Toward Human-Like AI

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***Abstract*—*Human-like AI* (*HLAI*) or *artificial general intelligence* (*AGI*) are AIs with humans' intellectual capabilities, and realizing HLAI to advance humans' civilization is one of Libgirl's mission. In this report, we'll summarize the progress of HLAI research of Libgirl. First, we'll describe our considerations to introduce the new term *HLAI*. After that, we'll briefly illustrate how we apply Later Wittgenstein as the philosophical foundations of HLAI. Some key concepts and questions of AI research will be described or answered in the discussions. After establishing the philosophical foundations, we'll introduce the *functional emotional developmental model*, which is proposed in <*The First Idea*>, as a paradigmatic developmental process of humans' intellectual capabilities. Such developmental process also shed light on the question: what primitive capabilities are required for HLAI? Besides the research progresses with high solidity, we'll illustrate the Rhythmic-Chaos Psyche Model, a hypothetical model of an intellectual individual. Finally, we'll sketch the roadmap for achieving HLAI, address some crucial questions to be answered in HLAI research, and address the promising technologies and scientific disciplines for achieving HLAI.**

***Index Terms*—Wittgenstein, Developmental Robotics, Epigenetic Robotics, Developmental Psychology, Functional Emotional Developmental Model, Spiking Neural Network.**

## I. Human-Like AI: What and Why?

People have such imagination to the ultimate AI: people command, and then the AI do the jobs. The scope of the jobs should be *general*, e.g. services, entertainment, tasks with danger, research, providing suggestions, taking care or helping people, and the AI should be able to *learn* any of them. In other words, we're dreaming of a program or robot that *learns*, *speaks*, *thinks*, has *creativity*, *empathy* and *common senses*—i.e., like a human. Therefore, to let us see clearly what indeed is the ultimate AI we are pursuing, human-like AI is the better terminology than Artificial General Intelligence or strong AI (what's general? how strong?). Also, the term "human-like" have philosophical significance, which will be illustrated in the following paragraphs.

## II. Wittgenstein Philosophy

On pursuing HLAI, we're asking such questions:

- What's *intelligence*?
- How can an individual *develop intelligence*?
- What's *understanding*?
- What's the essence of *language*?
- What's are *sensations* and *feelings*?

To avoid getting lost in the junggle of philosophy, we have to 'go right down to the foundations' and 'put the question marks deep enough down' (Wittgenstein, CV 62). Therefore, we adopt Wittgenstein's *ordinary language philosophy* via *grammatical investigations*, which is exhibited brilliantly in his latter work, <*Philosophical Investigations*> [1], to see clearly **what kind of activities are we doing** when asking these philosophical questions, **how should we descibe** these concepts and **what should we do** in our investigations. His philosophy, as a style and an approach, can be illustrated in this comments:

> 'Philosophy is a struggle against the bewitchment of our understanding by the resources of our language.' (PI §109)

By investigating how the words of the concepts are used in ordinary activities, how people acquire the skills of using these words, we not only are freed from the confusing philsophical theories, but also have a guide for the exploration into psychology and neuroscience, so then 'Since everything lies open to view, there is nothing to explain' (PI §126).

Wittgenstein philosophy can so shed lights on the questions above:

- *Understanding* the *meaning* of a *concept* is mastering its *uses* under the *circumstances*, but not construction of mental or internal representations and syntax.
- *Sensations* and *feelings* consists in how one acts on one's body states, others' behaviors or environments, but not names of inner objects or processes in a bearer.
- Intelligence consist in the capabilities to (learn to) play the *language-games* in human's *form of life*.

Now this question, "why human-like AI", can be answered: to make an AI with real intelligence is to make a language-games player in *human*'s form of life, so the AI have to be *human-like* in its practicing rationality, social capabilities and common senses. Moreover, although Wittgenstein didn't systematically describe how human develop the intellectual capabilities, there're still hints left:

> 'How does a human being learn the meaning of names of sensations? For example, of the word "pain". Here is one possibility: words are connected with the primitive, natural, expressions of sensation and used in their place. A child has hurt himself and he cries; then adults talk to him and teach him exclamations and, later, sentences. They teach the child new pain-behaviour.' (PI §244)

So we can have an image of the development:

- Since being, one interacts with the world by the innate abilities.

- By human nature, through experience and education, one integrates the innate abilities into complicated behaviors with language.
- One gradually extends one's linguistic abilities, i.e. knows more about the *form of life*.
- The instincts keeps driving one to play the *language-games*, to learn, to develop.

By nature and nurture, nuanced and complicated skills are built out of and used in the places of the inherent behaviors. It's in the differentiation of primitive desires and organization of sensory-motor skills that humans develop the capabilities of feeling, thinking and speaking.

In conclusion, by the holistic view we have from Wittgenstein philosophy, we can establish criteria of HLAIs:

- The Human-like Nature: the instinct or the potentiality to learn to live and build relationships with human.
- Robotic body: the capabilities to interact with the environments, sense its acts and act on its senses, and comunicate with human.
- Human-like appearances: the prerequisite for humans to treat it like treating a human and educate it.
- Education from us: to learn the *form of life*.

Though not completed in details, these criteria can serve as a guide for our exploration into psychology, neuroscience and computer science, and prevent us from confusions. Moreover, the requirement of a robotic body and developmental capabilities also show that *developmental robotics* is an important field of research for HLAI. While detailed *gramatical investigations* on some confusing concepts may still be needed, the philosophical problems of human-like AI is in principle resolved.

## III. Functional Emotional Developmental Model

Although in Wittgenstein philosophy, we can see *what* is intelligence, we still have to find out *how* is it developed in details. So here's the question: how one *learns* to play the *language-games* and inherit the *form of life*? Therefore, we introduce the *Functional Emotional Developmental Model* (*f/e model*) from <*The First Idea*> [2] as an outline of human-development and a guide for searching the inherent capabilities of an intelligent individual.

In the F/E model, emotions are considered as the bridge between *nature* and *nurture*, individual and *form of life*, and play a central role in developing intelligence, as we can see in Fig. 1. Under normal conditions, infants show primitive behaviors to the environments and their body states, and by the *form of life* of the caregivers, these primitive behaviors are regarded as *emotionally meaningful* expressions, so the caregivers will respond to or take actions for the infants, and the infants' experiences are shaped by the caregivers' form of life. Then the modified experiences serve as feedbacks to their behaviors, and the infants gradually modify their behaviors based on their inherent dispositions. Therefore, the experiences are considered as *emotionally enriched*. Through the consecutive interactions, with emotions as the bridge between the individual and the caregivers, gradually the individual's emotional expressions are differentiated into *emotional signaling* skills and the sensory-motor skills are organized into intellectual capabilities. Such processes of *Functional Emotional Development* are summarized in tab. I.

In conclusion, for the *how* question of *intelligence*, the f/e model provide us these important observations:

- Emotions guide the development of intelligence.
- Intelligence grows in enriching emotional skills.
- Form of life is inherited by affective interactions.

HLAIs have to be social-emotional beings. The social-emotional capabilities they need can be summarized by the three aspects:

- Functionality: the inherent behaviors of avoiding / approaching unpleasant / pleasant sensations.
- Disposition: the tendencies of behavioral change.
- Expression: the (especially facial or vocal) behaviors that induce social meanings to the educators and other people.

Therefore, to let HLAIs exhibit the human-like nature is to mimic these aspects of the social-emotional capabilities in terms of *grammar* in its design, so that the HLAI system develops the general intellectual capabilities through social-emotional development. By this viewpoint, we also maintain that to unravel the mystery of intelligence is to understand the physical, biological, and neurological mechanisms that prpoduce the social-emotional behaviors.

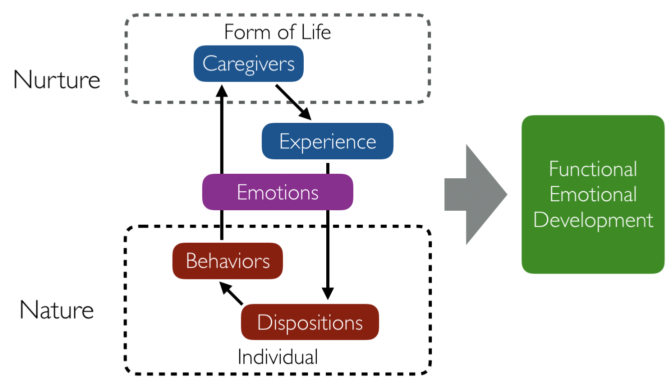


Fig. 1. The role *emotions* play between *nature* and *nurture*, individual and the *form of life*.

## IV. Rhythmic-Chaos Psyche Model

In the f/e developmental model, there're still questions unsolved. In development, children learn new skills day by day, like turning the head, moving limbs or the body, smiling to others, pointing at something, utterances—but how do they *start trying* all of these? Therefore, we hypothesized the *Rhythmic-Chaos Psyche Model*:

> The relation between human's biological mechanisms and behaviors should be viewed as a fusion of chaoticity and rhythmicity. The generation of behaviors are chaotic in nature, and through experiences,

TABLE I

The first 6 stages of *functional emotional development*. Benoted that by age 3, after the *linguistic explosion*, children already exhibit astonishing linguistic skills and some primitive logical thinkings.

| **Stage #** | **Starting Time** | **F/E Developmental Level** | **Emotional, Social, Intellectual Capacities** |
|---|---|---|---|
| 1 | from birth on | Interest in the world (Shared Attention, Regulation) | Pleasurable interest in sights, sound, touch, movement, and other sensory experiences. lead to looking. listening, calming, and awareness of the outer world and simple patterns. |
| 2 | from 2 to 4 months on | Fall in Love (Engaging & Relating) | Pleasurable feelings characterize relationships. Growing feeling of intimacy. The baby become more interested in the primary caregivers and begin to discriminate emotional interests, facial expressions & (any kind of) patterns. |
| 3 | from 4 to 8 months on | Intentionality (2-way intentional, emotional signaling & communication.) | A range of feelings become used in back-and-forth emotional signaling to convey intentions (e.g., reading and responding to emotional signals); the begging of "cause & effect", "logical" thinking. |
| 4 | from 9 to 18 months on | Multiple reciprocal Affective Interactions (Long chains of co-regulated emotional signaling, social problem solving, mood regualtion and the formation of a presymbolic self) | A continuous flow of emotional interactions to express wishes and needs and solve problems (e.g., to bring a caregiver by the hand to help find a toy):<br>1) Action level: Affective interactions organized into action or behavioral patterns to express a need, but not involving exchange of signals to any significant degree.<br>2) Fragmented level: little islands of intentional problem solving behavior.<br>3) Polarized level: organized patterns of behaviors that express only one or another feeling state, e.g., organized aggression and impulsivity or organized clinging, needy, dependent behavior, or organized fearful patterns.<br>4) Integrated level: different emotional patterns- dependency, assertiveness, pleasure, etc.- organized into integrated, problem-solving emotional interactions such as flirting, seeking closeness, and then getting help to find a needed object. More significant separation of perceptions from actions. |
| 5 | from 18 months on | Creating Symbols (using words, representation, ideas) | Experiences, including feelings, intentions, wishes, action patterns, etc., are put into words, pretend play, drawings, or other symbolic forms at different levels:<br>1) words and actions are used together (ideas are acted out in actions, but words are also used to signify the action).<br>2) Somatic or physical words are used to convey feeling state ("my muscles are exploding", "head is aching").<br>3) Action words are used instead of actions to convey intent ("hit you!").<br>4) Feelings are conveyed as real rather than as signals ("I'm mad", "Hungry", "Need a hug" as compared with "I feel mad" or "I feel hungry" or "I feel like I need a hug"). In the first instance, the feeling state demands action and is very close to action. While in the second one, it's more a signal for something going on inside that leads to a consideration of many possible thoughts and/or actions.<br>5) Global feeling states are expressed ("I feel awful", "I feel OK", etc.).<br>6) Polarized feelings states are expressed (feelings tends to be characterized as all good or all bad). |
| 6 | from 2.5 years on | Logical Thinking (Building bridges between symbols, emotional thinking, a sense of "reality") | Symbolized or represented experiences are connected together logically to enable thinking. This includes the ability for:<br>1) Differentiate feelings (gradually there are more and more subtle descriptions of feeling states- loneliness, sadness, annoyance, anger, delight, happiness. etc.).<br>2) creating connections between differentiated feeling states ("I feel angry when you are mad at me") and logical thinking ("The letters C, A, and T spell CAT").<br>Logical thinking leads to an enormous flowing of new skills, new games. |

learning and education, rhythm in the patterns of sensory-motor behaviors are built, and intelligence develops with building rhythm of larger time-scale and finer structures.

The overall relationship between the psyche and the environment is shown in Fig. 2, and here *psyche* indicates **the collective biological mechanisms that produce motions**. The *psyche* evolves with time, and the *sensations* from the *environment* decide the evolution from countless possibilities, as shown in Fig. 3; the *psyche* produce *motions* at every instant, and the *motions* affect the *environment*. Moreover, in observation and conceptualization, the psyche can be devided into *functions* with hierarchy, as shown in FIg. 4. The lower-level functions last shorter in time and are closer to sensory-motor responses, while the higher-level functions last longer in time and are closer to abstract thinking. Here in the conceptualization, we try to follow Wittgenstein's description to *concepts*: the capabilities to act and respond in a proper way with organized behaviors under circumstances.

The relationships between (higher-level) *meta*-functions and (lower-level) *sub*-functions are then illustrated in Fig. 5. Under a condition, the functioning of the sub-function may have little organization between the consecutive cycles, i.e. under high chaoticity; the meta-function then organize the functioning of sub-functions into systematic patterns, i.e. *surppresses* the chaoticity of the sub-function. The problem of *"start trying"* in children may also be explained by the development of their central neural systems, i.e. *myelination*. When the neural systems of a function is properly developed, the child has capabilities to exibit skills of the function; however, due to the undevelopment of the meta-function, the skills are then applied in a random or chaotic manner, or in more precise terms, diverges strongly over minor perturbations. Through the development of neural systems accompanied by experiences, the meta-functions are then formed to control the sub-functions, and the child then learned new concepts which are complicated organization of the more foundamental skills.

The Rhythmic-Chaos Psyche Model helps us to clarify the correspondence between psychological concepts and mathematical mechanisms. We can view the *psyche* as a dynamic sensory-motor controller, and we postulate that, when the *psyche* is in some attractor of the phase space of the system, an individual exhibit the behaviors that are regarded as being in some *mental state* or performing some *skills*, for the attractor decides how the individual acts and responses to the environment. Such interpretation fits the later Wittgenstein philosophy, as briefed in *Sensations and Feelings* of Sec. II. As explained previously, we can also describe *learning concepts* or *organizing knowledges* by development of meta-functions, and we can see the relationships between such functions as interaction and evolution between attractors. In these examples, the Rhythmic-Chaos Psyche Model serves as a general framework to bridge the gap between psychological concepts and mathematical mechanisms in a philosophically relevant way.

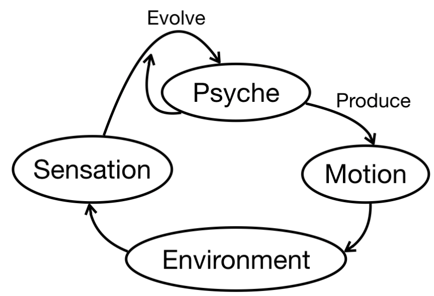


Fig. 2. The overall relationship bewteen the *psyche* and the *environment*.

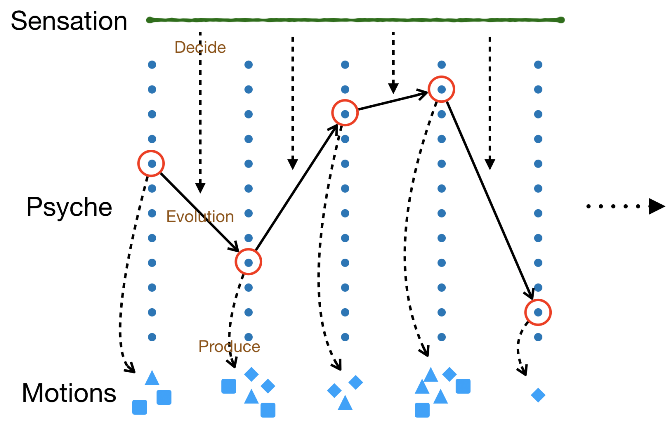


Fig. 3. In evolution of the *psyche*, *motions* are generated by the *psyche* at every instant, and *sensations* decide the *psyche* of the next instant among countless possibilities.

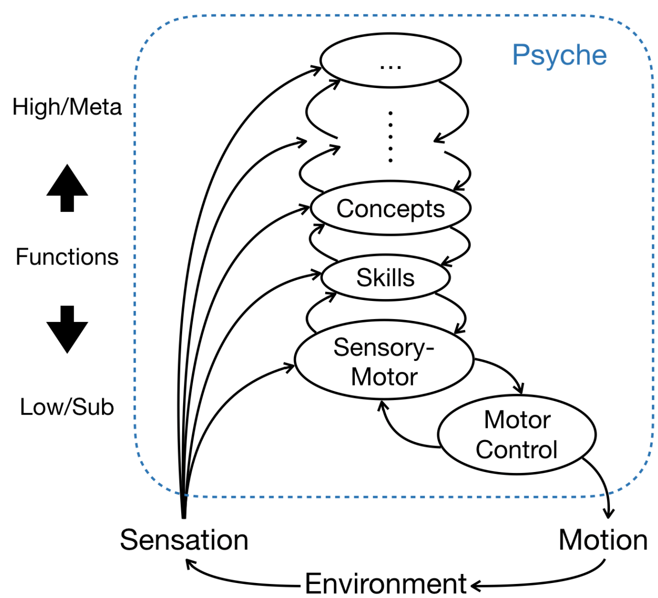


Fig. 4. The hierarchical conceptualization of the psyche by functions from low-level (sub) to high-level (meta).

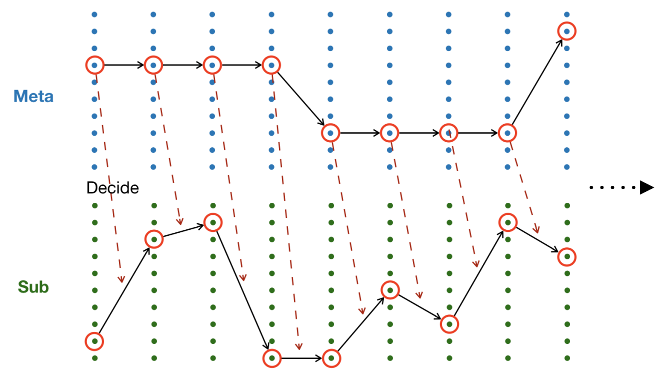


Fig. 5. Relationships between meta- and sub- functions: the meta-function suppresses the chaoticity of the sub-function.

## V. The Roadmap to Human-Like AI

Now we come to a summary to our current research progress. First, for criteria and descriptions, human-like AI is:

- A robot that sense, act and has a face.
- An social-being with emotional capabilities.
- An individual that develops with spontaneity, desire and intention.
- An agent who (leans to) play(s) the *language-games* in humans' *form of life*.

And the research roadmap to human-like AI is then:

1) Philosophical foundations.
2) Descriptions to the developmental processes.
3) System design of the artificial psyche.
4) Finding the necessary references to the physical, biology and neurological mechanisms required for implementing the psyche of HLAI.
5) Implementation including the psyche and sensory-motor system.
6) Experiments over system implementation and educational approaches.
7) Verifying the fulfillment of the criteria of human-like AI.

As illustrated in the report, step 1 is settled by Wittgenstein philosophy. Step 2 is mostly fulfilled by *functional emotional developmental model*, while more understanding to different types of emotions, and more case studies on human's intellectual and emotional development based on the inherent emotional capabilities are needed; we can only effectively progress to the next step with sufficient accomplishment in step 2. For step 3, *Rhythmic-Chaos Psyche Model* is proposed as a general framework as a starting point. For step 5, *developmental robotics* is a relevant source of references and technologies, and *Spiking Neural Network* may be a candidate of the model of the artifical psyche due to its intrinsic dynamic characteristics. After all above, we can start experimenting over system implementation and educational approaches. The human-like AI will be proven to be realized if some HLAIs are educated successfully as real intelligent beings.

Realizing human-like AI is one of the most challenging technology problems in this era. With this roadmap and the foundations we built, we can say we are a team, and possibly the only one team, that has a compass on the journey to human-like AI.

## References

[1] Ludwig Wittgenstein, Philosophical Investigations, 1953.
[2] Stanley I. Greenspan, Stuart G. Shanker, The First Idea: How Symbols, Language, and Intelligence Evolved from Our Primate Ancestors to Modern Humans. Da Capo Press, 2006.

# Principles of Intelligence

Outline Draft

(Shaka) Shih-Chia Chen

## Abstract

To answer how intelligence works, we have clarified the relationships between intelligence, learning, symbol, reasoning, thinking, rationality, emotion, judgment, taking action, consciousness, self, originality, depression, and wisdom. This is the only resource you can find in the world presenting a systematic knowledge for all concepts above. That means, when it comes to developing Artificial General Intelligence (AGI), we are super clear about what we're doing, while all the other teams in the world are in the mist. This supports that we can be the first team to achieve AGI.

### Notice

This is an outline draft for Libgirl team internal use. To make it publicly understandable requiring another work.

## Symbol as the central idea

### Definition of symbol

- A symbol is a set of fuzzy information packs from multimodal signal sources. We humans can recognize elements of one such set as the same symbol. In usual cases, we give common signs to indicate a symbol.
- We humans learn a symbol by associating information of the context. For example, flower's shape, smell, color, and social experience of passion. In most of the cases, a symbol is a pack of some past experience.
- When it comes to symbols in computer science, most of the time it means signs, not symbols.
- A category is a set whose elements are at least symbols. That is, we humans can't make categories for non processed fuzzy information.
- The detaily distinction between symbol, sign, category, classification, etc, shall be done by grammatical research, a method proposed by L. Wittgenstein.

## Thinking and Symbol

- We humans think using symbols.
- In a person's mind there are symbols. A person can observe different symbols and different combinations of symbols appear in his/her mind. The active or passive changing of these symbols in our mind, we call it thinking.
- When we humans think of a symbol at the moment, the symbol is a pack of past experience.
- After we humans think of a symbol, we can further decompose it into combinations of symbols.
- We humans can consciously group symbols. Learning from associating the symbol group, we create one more symbol.

## Abstraction

- Abstraction in its main sense is a conceptual process where general rules and concepts are derived from the usage and classification of specific examples. (Wikipedia Contributors, 2019a) However, one of the main differences between abstractions and pure generation is that the former is based on deriving new knowledge from seemingly unrelated data. (Rodriguez, 2019)
- But there is another critical viewpoint of abstraction. On the contrary to objectively deriving general rules or concepts from examples, abstraction can be also seen as a subjective process with which an individual stresses the common part of those examples.

It seems as if **empathy into the object** were the psychological process which brings the distinctiveness of the object into more than usually clear focus, and as if **abstraction from the object** were the psychological process most calculated to blind one's eyes to the distinctiveness of individual things in favour of their general similarity, which is the actual foundation of the idea. (Jung, 1921/2017, p. 60)

- Of course we want objective facts. However, in the real world no observation is purely objective. Thus, this article takes the viewpoint that real world abstraction is a subjective process emphasizing the similarity between observations.
- Abstraction makes a person able to see things as the same in his/her mind. Like, subjectively seeing a never seen object as a chair. As long as there are enough people sharing similar abstraction processes, people agree those objects having shared properties. People then say those objects ARE chairs, even if it's in fact a subjective abstraction with social consensus.

- With this critical perspective, we can propose the mechanism behind the real world abstraction ability. Upon that, we can show how to make the machine with the ability to do abstraction.

## Symbol and Abstraction

- Recognizing individual information segments as the same symbol is an abstraction process, subjectively seeing things as the same one.
- Since abstraction is subjective, individual segments seen as the same symbol can be seen as different symbols in another context.

## Why We Humans can't Consciously Capture the Way of Symbol Recognition

- Examine this with your own experience. To be conscious of some mental target, the mental target has to be present in our mind for some long enough time interval. The shorter the mental target stays in our mind, the less we're consious of it.
- Yet, in our mind, the existence of the mental target is a problem. When can we say "there is ONE mental target" or they are multiple fuzzy thoughts?
- That is, before we are conscious of some mental target, there should already be some fuzzy information segments recognized as the SAME mental target.
- Then, during we are conscious of that mental target, our mind continuously recognizing the fuzzy information segments as something the SAME.
- These fuzzy information segments recognized as the same one is a symbol appearing in our mind.
- So, we can't intuitively understand how symbol recognition happens because all we can be conscious of are already symbols. We can't be conscious of those fuzzy information segments before they become some symbol.

## Consciousness

- The continuum of all information segments, that a person can be conscious of as symbols, is the person's consciousness.
- This explanation is similar to William James' "stream of consciousness."

## With Symbols, We Human Have the Ability to do reasoning

- When there are some perceptual materials, a person recognizes them as some combination of symbols. Most of the symbols correspond to past experiences.
- Decomposing new perceptual materials into a combination of symbols that corresponds to past experiences, we humans can react to new conditions according to past experience.

- After a person thinks of a symbol, the person can further decompose its associated perceptual materials into another combination of symbols. Doing this multiple times, the person can establish kinds of relational network of symbols.
- This recursable decompositional matching we call it reasoning.

## Learning Symbols with Associative Learning

- We humans learn a symbol by associating information segments that appear at the same moment. We can say this learning process is associative learning in the broadest sense (Encyclopædia Britannica Contributors, 2020).
- Associative learning is about remembering packs of information, so part of the information can recall other associated information. For example, when a person smells a flower's odor, he or she can think of its name or shape. A person learns an association in his or her past experience.
- Notice that humans' associative learning is beyond classical conditioning. That is, time reverse order relationships can be learned by humans' associative learning (Lipkens et al., 1993).
- We humans communicate mainly in vocal language, so we apply language signs with voice to represent most of the symbols. For example, we use the word "flower" as the sign to represent the symbol including flower's shape, flower's smell, text spelling of flower, etc.
- Applying associative learning on symbols appearing in our mind, we can learn more complicated symbols. For example, to learn that "cryptocurrencies" are types of "currencies" based on "blockchain" technology.

## Social Consensus on the Ability to Use Symbols

- Whether or not a person has the ability to use symbols requires behavioral judgement that can be observed according to social consensus.
- Even though a person (or a robot) can learn symbols with associative learning, we still have to design suitable lessons (data) to make the society admit that the person (or the robot) has the ability to use symbols in observable behaviors.
- The behaviors a person (or a robot) should be able to do to prove to the society include
    - Telling the meaning of a symbol. That is, the ability to do expressions like "the meaning of X is Y" or "X is Y".
    - Assigning a value to a symbol in an expression. Such as, "assuming the stone is an apple."
    - Operating values on a combination of symbols in an expression. Such as,
        - "A red apple" constructs an image of an apple whose color is red.
        - "Assuming the stone is an apple, is the stone a food? Yes, the stone is food." This expression transfers the properties of the 'apple' to the 'stone'.

# We Humans Won’t Have Consensus about How Biological Neural Activities Represent Symbols

- The representation of a symbol can be traced to the BEHAVIOR OF a population of biological neurons. In some extreme cases, it is not impossible to trace symbol recognitions to one single neuron, the grandmother cell phenomenon for example (Wikipedia Contributors, 2019b), even if this should be extremely rare. Notice that, the representional encoding is another issue.
- When it comes to being acknowledged in human society, whether or not a neural network, biological or artificial, has learnt a symbol, is a social consensus instead of some definite standard.
- Whether or not a neural network, biological or artificial, shows consistent behavior that can represent a symbol recognizer, is decided by how a group of humans interprets its behavior.
- We say AI engineers train artificial neural networks. In fact, It’s not a single direction that AI engineers train an artificial neural network. It’s a bidirectional relationship. The so called “training process” is actually a consensus establishment process between AI engineers, product managers, users, and society. What the behavior of this artificial neural network means, or whether or not the training is successful, is social communication work.
- Back to biological neurons, whether or not a biological neural network has learnt a symbol is also a social communication work. Plus, we humans don’t have consensus on the meaning of most of the specific symbols. As a result, in real world case, we humans won’t have consensus about how biological neural activities represent symbols. For example, “you are great” for a person can be a positive expression like. Yet, “you are great” for people with depression can always give negative sentiment. Of course, researchers would like to draw a boundary between healthy people and people with depression. Still, such boundary is another case of reaching social consensus.
- There are still values trying to build the symbol representation map of our human brain given assumptions or contexts. We just have to remember, all the symbol representation maps have their limitations in real world situations.
- In contrast to building the symbol representation maps, it’s more practicall to directly obtain the correspondence between symbol and behavior, which is in my viewpoint the essence of L. Wittgenstein’s grammatical research. Notice that L. Wittgenstein’s terminology “grammatical” is different from common Linguistic definition. In my understanding, “Grammar” in L. Wittgenstein’s philosophy is a general term indicating the structures of daily used multimodal language.
- As simplification for reasoning, even if we humans won’t have consensus about how exactly neurons present specific symbols, in this article I still say the usage of a symbol can be traced to the behavior of a population of biological or artificial neurons.

# Universality of Spike-Timing-Dependent-Plasticity (STDP) as the Neural Model of Associative Learning

There are many materials supporting that STDP can do associative learning. (Milo et al., 2017) (Albers et al., 2013) (Guo et al., 2014)
Thus, STDP is a universal neural model of associative learning. That is, we can implement associative learning by neural network programs with STDP algorithm.

## Why We Need a Universality

There is NO actual universal mechanism in Biological phenomena or real world engineering because they are composed of almost chaotic facts or dirty works. Furthermore, learning is one of the most diverse activities. To have efficient solutions with Anti-fragility (Taleb, 2012) according to various contexts, biological creatures or engineering products tend to possess multiple or even seemingly conflicted properties in the same organ. We should expect the same for biological learning mechanisms (Suvrathan, 2019) or practical machine learning methodologies.
Even so, there are two benefits of providing such universality. First, we can have a simplified model for reasoning, like the theoretical functionality of Turing Machine. Second, we can have a default solution before optimizing the machine product according to contexts. For example, even if in the human brain glia cells do contribute to formation, operation and adaptation of neural circuitry (Allen & Barres, 2009), it’s not a must for A.I. software to incorporate glia cells given the universality of artificial neural networks.
Therefore, on the seemingly contradictory viewpoint that we said there is NO universal mechanism, which stresses the complexity of reality, we still use STDP as the universal neural model of associative learning.

## Supervised Learning by STDP

There are many ways to achieve supervised learning using STDP. For example, to provide teacher signals in a supervision layer. (Hao et al., 2020)

## Reinforcement Learning by STDP

Dopamine-modulated STDP can achieve reinforcement learning (Izhikevich, 2007)

# Emotions

- There are three aspects of emotions: tendency, expression, and neural learning mechanism.

- For example, the tendency of happiness is the movement toward the source that makes individuals happy. The expressions of happiness include smiling. And, the neural learning mechanism of happiness is the modulation of associative learning by the reward signal.

# From Symbol to Action

## Association, Thinking and Rationality

- Thinking is the process that the combination of symbols is changing at the moment.
- Purposeless thinking is association.
- Rational thinking is a way of association that is based on the latter's correctness.
- Through rational thinking, we can describe the association and hierarchical relationship between symbols.
- Training an individual to have socially acceptable rationality is to guide the individual's thinking process with education according to social correctness. Associative learning happens during education with or without reward and punishment. After training, an individual's thinking process tends to be converge, stable or become rigid.
- However, it is extremely difficult for an artificial system to possess the potential to continuously learn multiple skills yet still have the tendency to converge.

## Meaningful and Rational

- Whether a statement is meaningful or not replies on our ability to use rational thinking to construct the relationship between the symbols in the statement.
- However, whether a thinking process is rational or not depends on social consensus. There is no absolute standard to judge whether a statement is meaningful or not.
- We can say "Colorless green ideas sleep furiously." (Noam Chomsky, 1957/2015) is meaningless because in the general social consensus, 1. Green is colorful, not colorless. 2. Color property doesn't apply to ideas 3. Ideas cannot sleep, only creatures can. 4. We cannot sleep in a furious way — being furious and then "beating people" is a more natural situation.
- So beyond the general social consensus, "Colorless green ideas sleep furiously." can be meaningful. Society gives artists and poets more freedom against general social consensus.

## Judgment and Action

- Making a decision is a process in which the choice of symbols in thinking corresponds to different actions.

- For example, thinking "go left" and "go right" cannot trigger action at the same time. By deleting one of them from the mind, the remaining symbol can directly lead to action execution.
- Deleting/keeping which symbol in the mind can be results of learned habits, rational thinking, or emotional impulses.
- The linkage between symbol in the mind and certain action is neither nearly instinct or being formed by associative learning.

# Self-concept

- Self-concept is a symbol about the individual him/herself.
- The distinction between self and non-self can be strengthened or reduced by learning.
- Education can change a person to be more selfish or less selfish.
- In fact, the self-concept is just a symbol. The boundary of self is fuzzy.

# Originality and Rationality

- Original ideas require unexpected thinking, which must go beyond rationality.
- Because rationality makes an individual's thinking conform to the correctness of social consensus, it can lead to converge, stability or rigidity.
- As a result, children or young people are more likely to have original ideas because they tend to be less rational.
- Still, adults can have originality.
- There are other mechanisms than associative learning in biological brains. Enriched environment can lead to neurogenesis in the brains of adult rats. (Nilsson et al., 1999)
- While originality is irrational to the society and hardly accepted, adults have the responsiblity to turn the creative result into a more social acceptable form.

# Depression and Intelligence

- Depression happens when someone has learnt a closed loop of negative thinking. This thinking process is likely to be rational.
- Here comes an example. First, the subject has learnt a strong association between thought patterns "don't do xxx" and "I am wrong that I do xxx". Second, the subject has learnt another association bewteen the thought pattern "I am wrong about xxx", feeling guilty, and telling the subject him/herself “don’t do xxx”. Then, the negative thinking loop is present. If this is the case, when another person tells "Don't blame yourself" to the subject who is blaming him/herself, the negative thinking loop hardly stops. It causes the subject to think about "I am wrong that I’m blaming myself" but the subject can’t help feel guilty and to tell him/herself “don’t blame myself”. However, this triggers another “don’t do xxx” and becomes an endless loop of suffering.

- Given the case above, even if “don’t blame yourself” is a neutral or positive expression, it can continue to strengthen the cycle of negative thinking and negative action taking by depression patients.
- We cannot ask these patients to be responsible to their way of thinking because the communication way of "asking them to be responsible" will only make depression patients worse in reality.
- At this moment, drugs or special psychotherapy can be considered.
- Not everyone will suffer from depression because each person's life exerience and learning strength is not the same.

## From Intelligence to Wisdom

- Intelligence is the manifestation of the thinking and learning abilities mentioned above.
- Wisdom is to know the limitations of thinking, learning, and intelligence so that we do not over rely on thinking and self-concept.
- With wisdom, we can take the best actions for individuals and groups in the long run.

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# Libgirl Spiking Neural Network Technology: Research and Open Source Project

## Abstract

Spiking Neural Network (SNN) is regarded as the 3rd generation of neural network models for its computational power, computing efficiency, bio-plausibility and dynamic nature. Based on our research on humanlike AI (i.e. AGI), we also regard SNN as the best choice of computing model. However, the development of SNN technologies is still limited due to the lack of effective training algorithms.
Through our research, we proposed the causality-reversal algorithm, which is promising to serve as a general supervised learning algorithm for dynamic tasks, and also the foundation of other scenarios of training. For implementing the novel algorithms with high computing performance and good programming productivity, we start the open source project WheatNNLeek. We develop the project by the combination of Rust, which is a system-level language with leading security by its design, and Common Lisp, which is flexible and facilitates fast prototyping. We aim to advance and advocate the SNN technology by the causality-reversal algorithm and the WheatNNLeek project.

## Introduction

Spiking Neural Network (SNN) is regarded as the 3rd generation of neural network models[7], and was mainly developed for simulating biological neurons. An SNN is composed of spiking neurons and synaptic connections between them.

For a single spiking neuron, it’s membrane potential evolves over time by dynamics (e.g. differential equations over time). When the potential exceeds the threshold, a neuron fires (exhibit a spike on the membrane potential) and sends neurotransmitters to the downstream neurons to effect their potential [1,3].

For topology, i.e. the structure of the connections, normal non-spiking neural networks (i.e. Artificial Neural Networks) are layered and feedforward. On SNN, there’s no explicit constraint, so SNNs’ topology are fully designed by its purpose and application, e.g. mimicking biological neural systems or fitting the spatial pattern of data [1, 4-6].

For information processing, SNN can process information not only by firing rate, which is mathematically equivalent to non-spiking ANNs[1]. SNN also process information by other temporal coding mechanisms, i.e. by precise spike times. The temporal coding mechanisms includes time to first spike, phase, or synchrony. These encoding let SNNs be more computationally powerful biologically and biological plausible[1].

The models of SNN synapses are also powerful for both information processing and learning. By short term synaptic plasticity that models the neural transmitter propagation, the synapses are also time sensitive and have the capability of memory [8,10]. SNNs has also various biologically plausible learning rules developed from the Hebbian rule, and these learning rules can be applied for unsupervised or reinforcement learning[1, 9]. Various supervised learning algorithms are developed, while it's still a challenge to develop one which is efficient for SNNs with deep layers or recurrent topologies [1].

Successful business applications of SNN technology is now emerging, and *brainchip* is an example[11]. By SNN algorithms and neuromorphic computing hardwares, they provide pattern recognition solutions that learns rapidly with much fewer data, inference with high accuracy and have low computing overhead.

In summary, SNNs has these potential and advantages:

- SNN is biologically plausible, so it's more applicable to transfer the knowledge of neural science to technologies.
- For its dynamic nature, SNN is suitable for real-time or interactive scenarios, e.g. robotics, autonomous car, human-machine interaction, conversation, real-time detection and recognition.
- SNNs are more cost effective for computing, For SNNs are composed of independently evolving spiking neurons, they are suitable for full parallel computing. By the intra- and inter- neuron dynamics, SNNs are computationally powerful, so the required total number of neurons can also be reduced. The event-based nature of information propagation between neurons are also computationally efficient. Neuromorphic chips[3] can accelerate the computation further.

Although SNN has those promising properties, its development is still limited due to the lack of general supervised learning & reinforcement learning algorithms[1,2], and we are developing CR (causality-reversal) learning algorithm, a general supervised learning algorithm for SNN, to advance the technology.

# Causality-Reversal Learning Algorithm

By the CR algorithm, the methodology is as below:

- Perform the training with reversed time.
- Calculate the error at the output neurons.
- Propagate the error back based on the weights of connections and the activities of upstream neurons.
- On the firing upstream neurons, modify the weights based on the error on the downstream neuron.

Currently the mathematical formulation is done and the implementation ongoing. We also have a reinforcement learning algorithm in the stage of conceptual formulation. Here's a glance of the mathematical formulation.

Dynamics in forward-time operation:

$$\frac{dV_f^i}{dt} = D_n^i(V_f^i, I_f^i), V_f^i \leftarrow V_{reset}, \text{ at } t_{fire}^i. \tag{1}$$

Dynamics in reverse-time operation:

$$\frac{dV_b^i}{dt} = D_n^i(V_b^i, I_f^i + I_b^i) + \delta(t_{fire}^i)(-V_{drop}) + D_{en}^i. \tag{2}$$

$$I_b^i = \frac{V_b^i - V_f^i}{\tau_b^i}. \tag{3}$$

$$\Delta V_{inj}^{i,k} = \begin{cases} \Delta V_{inj}^i w^{i,k} \gamma^k, \text{ in rest state.} \\ 0, \text{ in refractory state.} \end{cases} \tag{4}$$

$$D_{en}^{i,k} = I_b^k \frac{(\Delta V_{inj}^{i,k})^2}{\sum_{l,x}^{l=back} (\Delta V_{inj}^{l,k})^2 (\tau - \tau_d^{l,k})}. \tag{5}$$

$$D_{en}^i = \frac{V_{drop}}{N_{back}} \sum_{i,k}^{k=fwd} \frac{D_{en}^{i,k}}{\Delta V_{inj}^{i,k}}. \tag{6}$$

# WheatNNLeek Open Source SNN Project

For developing the new learning algorithms, we need complete flexibility and autonomy on development, so we decided to build a new SNN framework but not developing our new algorithm on an existing one. For WheatNNLeek, we choose Rust, one of the fast-growing programming language, as the low-level language for its high performance, good maintainability and programming productivity. In addition, we use Common Lisp as the high-level scripting language, for its powerful REPL facilitate experiments and its macro system make it easy to make a domain specific language.

# Conclusion

To advance the SNN technology from scientifically promising to production-applicable, we are developing causality-reversal learning algorithm, which aims to be a general supervised learning algorithm and also the foundation of other categories of learning algorithms. The mathematical formulation is done and the implementation ongoing. We're also developing the open source project WheatNNLeek with the combination of Rust and Common Lisp to fulfill the need of performance, productivity and flexibility. By our research and development, we aim to take a leading role on the next generation of neural network technology.

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# Abstract

Dong is a machine learning operation (MLOps) platform emphasizing user experience (UX) for machine learning developers.
We aimed to create the Rails-Heroku combination for machine learning.
This product supports the Libgirl team not only has engineering, UX energy like Heroku, but also has machine learning knowledge so we can make a machine learning development platform.

# Introduction

## Problems of machine learning applications

1. Lack of total integration standard resulting
   a. low project deployment ratio: 12% (Bughin et al., 2017)
   b. high technical debt:
      Knight Capital's system losing $465 million in 45 minutes, …… from obsolete experimental codepaths. (D. Sculley et al., 2015)
   c. low production efficiency:
      3–12 months to see the light of a production deployment. (Faria, 2019)
2. Developers or scientists don't want a total integration standard because of non flexibility and lack of short-term incentives.

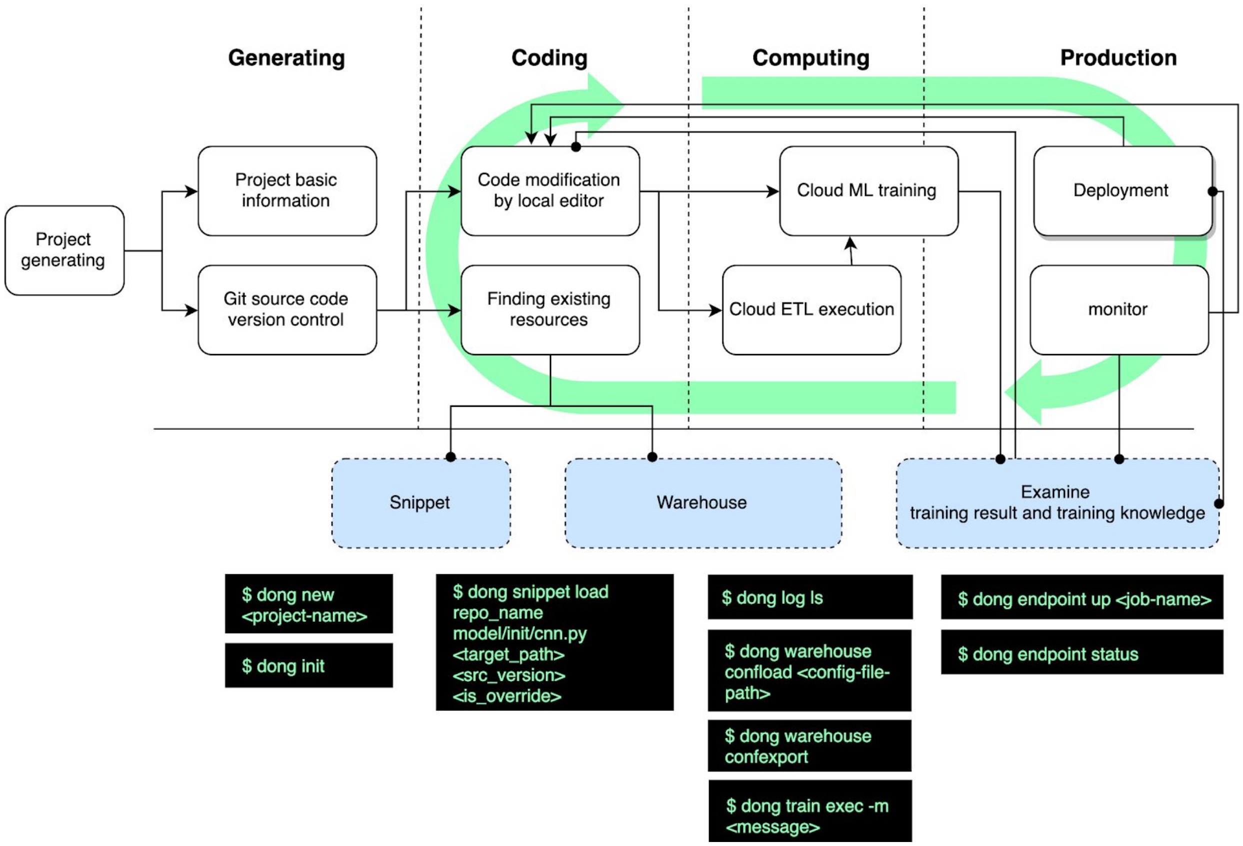
## Dong's Differential Values

Dong consists of
1. Dong Framework - a MLOps project framework.
2. Dong Cloud - a MLOps cloud service for managing cloud training/deployment of a Dong Framework project.
3. Dong CLI - a client side command line tool to quickly build or execute a Dong Framework project on local test or on Dong Cloud.

Dong is an organic MLOps with balance between being **organized**, being **integrated**, yet being **adaptable**.

We achieved being organized and integrated by introducing ML project level framework and training knowledge framework. Besides, we achieved being adaptable by code snippet functionality.

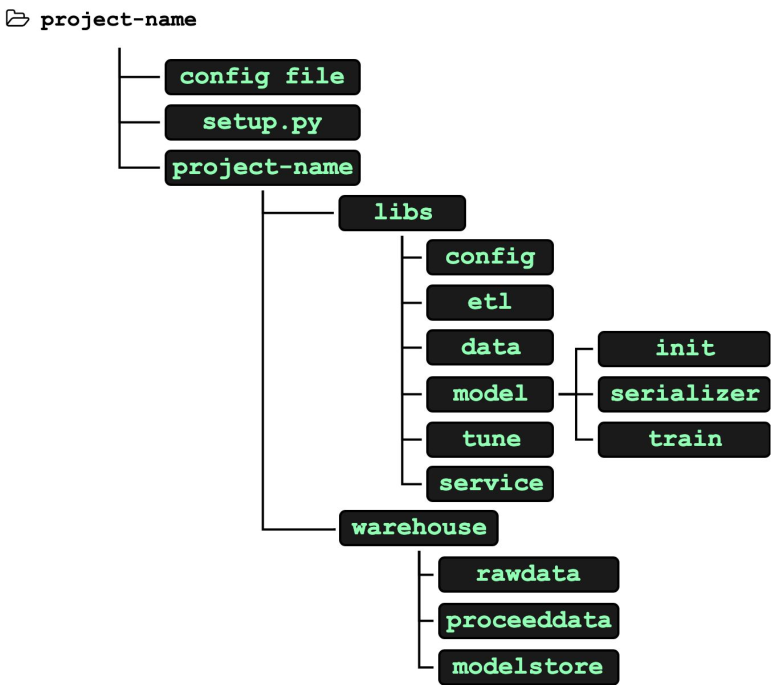
# Workflow




## Project Generating

```
$ dong new/init [PROJECT_NAME]
```

This creates a machine learning project with the following structure.




## Coding

Fast coding from snippets.

```
$ dong snippet load [REPO_NAME] [FILEPATH]
```

### For example

```
$ dong snippet load baliuzeger/dong-snippets data/c.py --src=origin
```

This command loads a code file snippet into the current project directory from https://github.com/baliuzeger/dong-snippets/blob/master/data/c.py

## Cloud Training

```
$ dong train exec
```

This will upload the current dong machine learning project and execute training on Dong Cloud. For example,

```
$ dong train exec -m "dong train exec" -- --config-module default

Use dong ML project: dong_mnist_example
Project path: /private/tmp/dong_mnist_example
Building package...
```

```
Uploading package...
Job name: [TRAIN_JOB_NAME]
```

## Model Inference HTTP Endpoint Deployment

```
$ dong endpoint up TRAIN_JOB_NAME
Bring up...
New endpoint name: ENDPOINT_NAME
```

Then you can do HTTP requests to ENDPOINT_IP to do model inference.

## Check Status

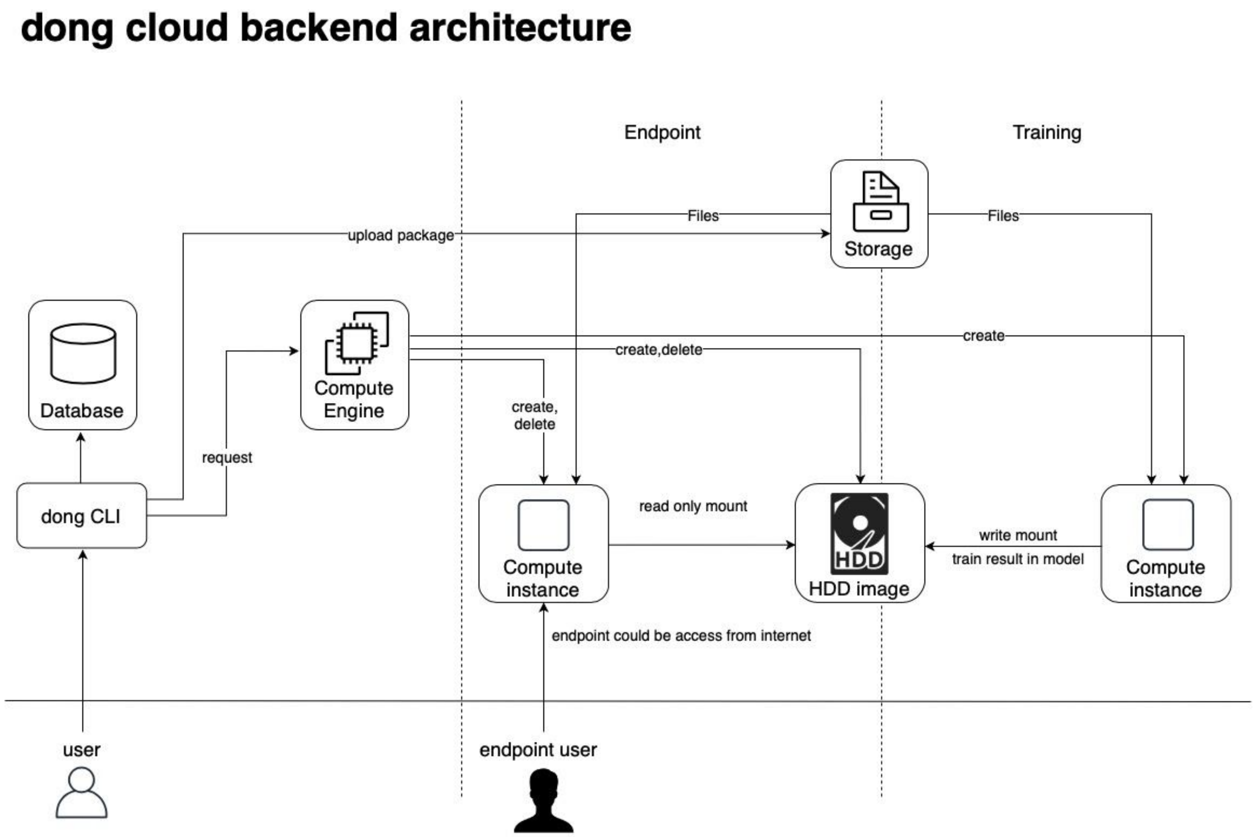
### Check a Training Job Status

```
$ dong train status -j TRAIN_JOB_NAME
name: TRAIN_JOB_NAME
message: my first dong train exec
status: Succeeded
```

### Check a HTTP Endpoint Status

```
$ dong endpoint status -e ENDPOINT_NAME
Endpoint name: ENDPOINT_NAME
External ip: SOME_IP
Status: Preparing
```

# System Architecture




# Conclusion

Dong product proves that Libgirl team has the technological ability to develop and operate a machine learning PAAS service.

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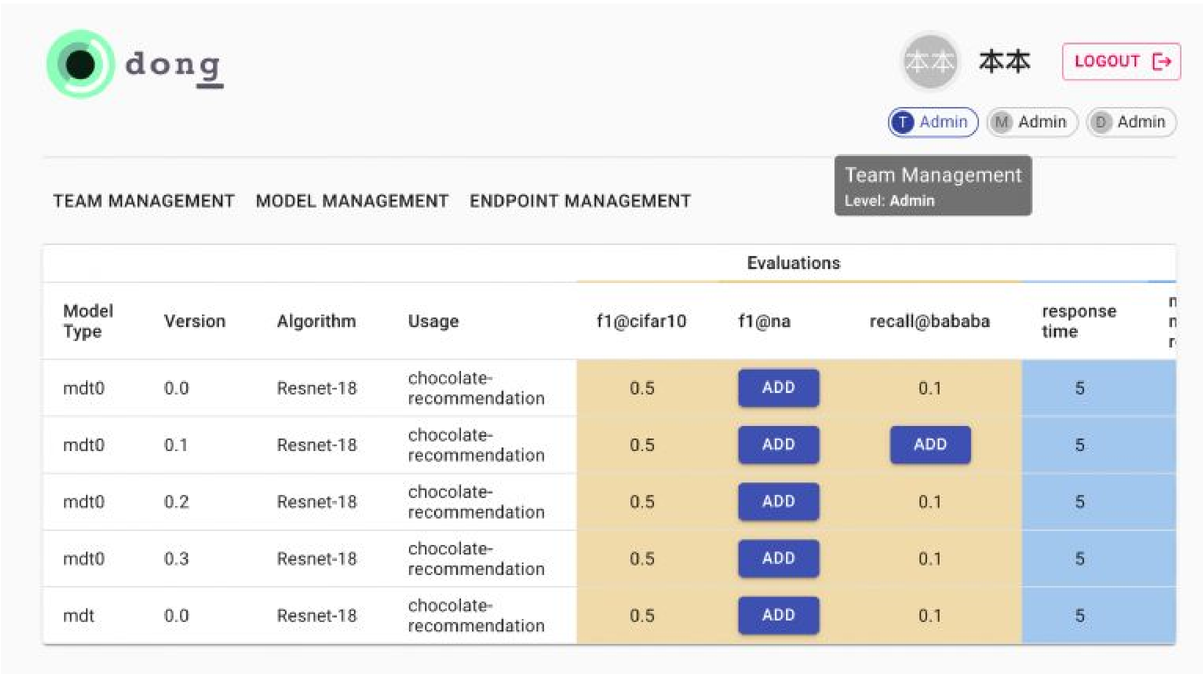
# Donut: MLOps Meets Domain-Driven Design

## 0. Abstract


Donut is an easy-to-use tool that fits all your needs for machine learning model management. Serving the crucial part to record and present every ML model knowledge and evaluation for visually control with hierarchical access setting. Generate API for deployment and record the deployment configuration and metrics, to fit the full collaboration across whole ML model production.

Using Domain-Driven Design (DDD), we could meet users' needs and have well-organized coding at the same time. The business logic is also maintained in the development.


Donut's dashboard

See [Donut's website] for a product tour.

# 1. Introductions to MLOps and DDD

## What is MLOps?

MLOps is Machine Learning plus DevOps. In ML engineers / data scientists' daily life, keeping different models / experiments in mind would be a big problem. It's NOT easy at all since we'll have all the following things to do:

- Controlling versions
- Making different trial with distinct datasets
- Tuning model with sets of hyperparameters
- Tell FAEs which model to serve is the best for specific scenarios
- Show a comparison of models to your boss
- ... and more

To solve the above problems, MLOps is a must-have product.

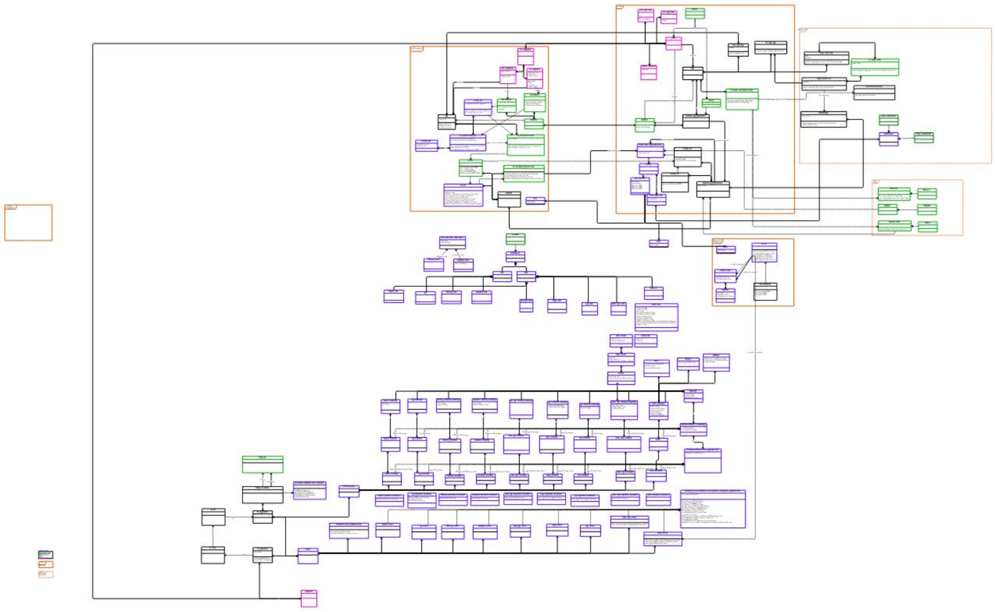
## What is DDD?

Domain-Driven Design helps the domain experts and the software engineers to collaborate, establish consensus and deliver a product that truly meets the needs. Domain experts know what to do to solve the domain problems, but the know-how is usually implicit and context-dependent and making abstraction and deterministic algorithms are usually not the common practices for them. On the other hand, the software engineers know the engineer techniques, but they don’t understand the domain, so the ambiguity of the domain-specific concepts may lead the engineers to deliver products that misfit the needs. To solve such problems, DDD provides strategies and tools to facilitate the cross-discipline collaboration between domain expert and software engineers, so that after both sides work together to build the ubiquitous language, the domain expert can convey the meaning of domain knowledge with proper abstraction, the software engineers can implement the domain logic correctly, and both of them can explore the best solutions and implementations together.

By implementing Donut with DDD, we systematically investigate the domain knowledge of machine learning to find out the true solutions for all the roles in the MLOps work field. In conclusion, the solutions can be delivered by managing user permission, machine learning model knowledge, and service endpoints.

## 2. Core Value of Donut Model Management System

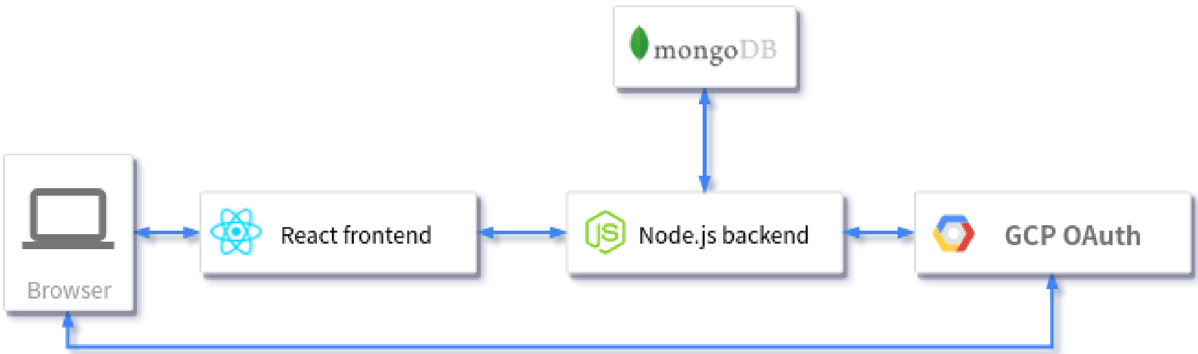
Donut is an MLOps tool focusing on Model Management and follows DDD (Domain-Driven Design) By communicating with ubiquitous language, we construct a solid tool that meets people's needs across different specialists, including ML engineers, data scientists, FAEs, and so on. Through the whole developing process, we've well-investigated what is machine learning model, what is the inference algorithm, how the algorithm / dataset / model / team management interacts with each other. For example, we detailly defined the structure of a model, separating the inferencing algorithm from the usage of a model. This makes models easy to sort and compare and make a huge difference from other MLOps tools, saving your time managing all the pieces of stuff and collaborating with your teammates!



Donut's DDD Diagram

## 3. Structure and Features

The general structure of Donut is shown in the following picture:
The user could use a browser to connect to Donut's dashboard, using Google OAuth to log in, manage your model and training result through its React frontend. While an operation is submitted, the frontend would send an API request to its Node.js backend service, checking the correctness and apply operation in the MongoDB database.




Donut's Basic Structure

The main features of Donut included 3 parts:

- Team Management
  - Control accounts and set permissions
  - Easy for management, separated permissions would suit different roles

- Model Management
  - Register your models
  - Do sorting / version control / management / comparison

- Deployment Management (Under Construction)
  - Utils for deployment
  - Combine with container

## Team Management

Donut provides Team Management of member control for administration authority, which uses level structures to control account / model / deployment. A person could do the corresponding actions if and only if he or she has the correct Team Management / Model Management / Deploy Management level. Under strict authority control, team members could be well organized and wouldn't have any authority not fitting his / her role. Model Management is also under authority control through one's Model Management Level (MM Level) and Deployment Management Level (DM Level) also is, too. See Donut Domain Rules and Donut Permission Design for detail definitions.

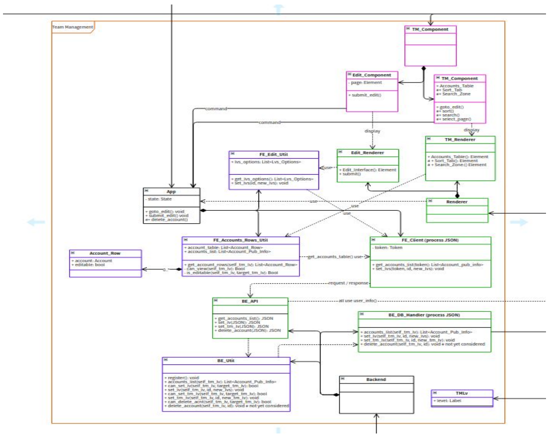
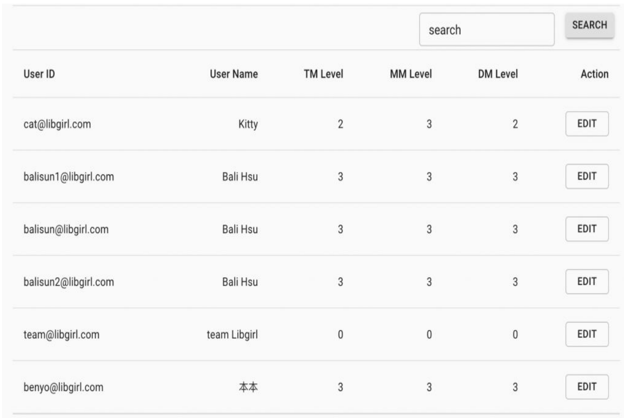


Diagram for Team Management



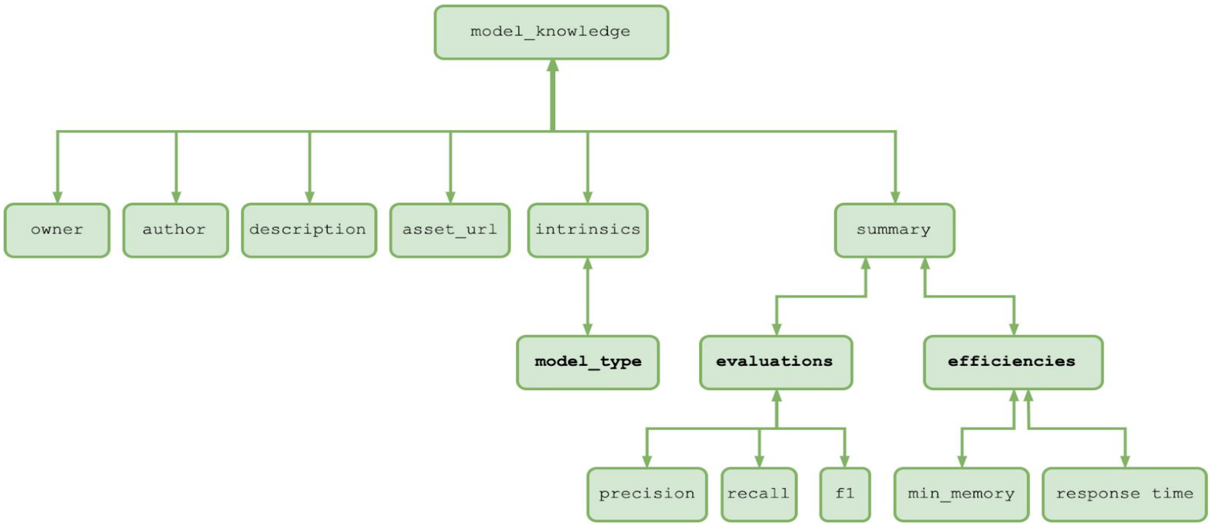
Team Management dashboard (with filter available)

## Model Management

In Model Management, Donut provides things you need to record for a model, after entering the first one, your next version of the model would automatically be filled in and construct dependency with the former versions. A series of models will have their shared model_type, which is composed of the following elements:

- name / owner / description
- inference algorithm (e.g. resnet-152 / alexnet / decision tree...etc)
- usage
  - description (usage for the model)
  - input_type
  - output_type
- versions (hash of the models)

While a series of models share the same model_type, they would have different attributes since using different data to train. Users can detailly enter the description for a particular model and fill in their evaluations (e.g. precision / recall / f1 score) and efficiencies (e.g. min memory requirement / serving response time). They are all customizable. Donut supports registering / removing / editing all the records while it doesn't store the model the user has trained. In fact, most of the AI companies want to have an easy-to-use tool to manage all the training models, but they want to keep their data within the company for privacy and security reason. Since then, Donut is designed as an on-premise tool and only record the asset_url for your model instead of storing the model itself at the local server so that the risk of exposing their important models won't increase.




A model's model_knowledge structure

We have carefully taken care of the dependency and authority with database checking so that users won't be able to remove occupied items or models that are NOT created by the owner or still have dependencies. For detail CRUD specifications, please also see Donut Domain Rules. For a detailed diagram, please see "DDD_Diagram" in donut_MVP_DDD_diagram.

### Deployment Management (Under Construction)

Although still under construction, we've finished the permission control part for Deployment Management.

## 4. Conclusion and Outlook

Donut is the DDD's success story on the MLOps domain. It solves not only model management problems but also helps teams to well organize their authority control. We'll have some future plans to make Donut better and add some more features, including but not limited to service deployment, training tool integration, Docker services, integration with training tools (Kubeflow / Jupyter / Polynote), tags / advanced search / model pins, etc.

# Libgirl Bot: Your Smart Robot Friend

## 0. Abstract

Empower by AI, Libgirl Bot put you through the whole internet with a conversable friend accompanying all day long, not only as a Siri / Alexa-like assistant. Friends share news, friends share knowledge, and provide help in daily life. Talk to her, and find how versatile she is!

The main structure of Libgirl Bot is established on AWS and it responds to requests from FB & Line, we'll have a web version in the future. To see what it runs like, check out our online running versions at FB messenger or Line. We initialized the project on Oct 29 (2019) and on Nov 25 we arranged all our RDs in. We successfully launched the Libgirl Bot on Nov 28.

## 1. Structure

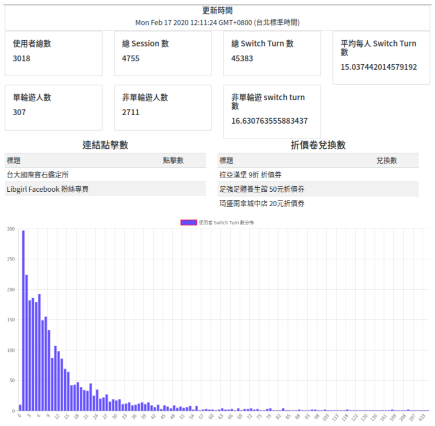
The Structure of Libgirl Bot can be separated into the following components:

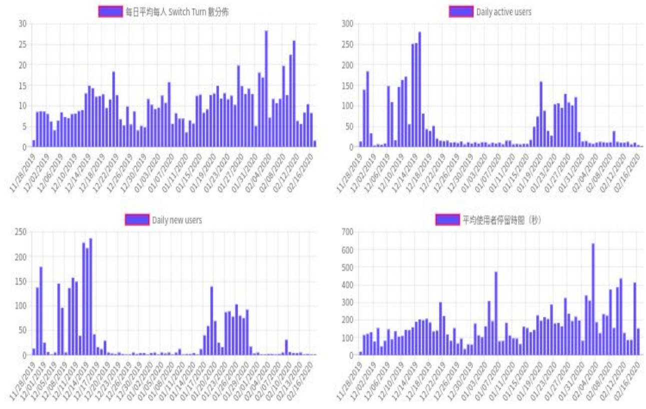
- Frontend Messenger: FB Messenger and LINE. After receiving a message from a user, the IM platforms will send requests with the message inside to our chatbot.

- Chatbot: Receives requests from FB / LINE, makes requests to the IM platforms to show the signs of “read & typing” to the users, generate reply messages, make requests to the IM platforms for sending replies, and save the conversations into the database. The service is written in Node.js (typescript) and deployed on AWS Lambda, while the database is also on AWS (DynamoDB)

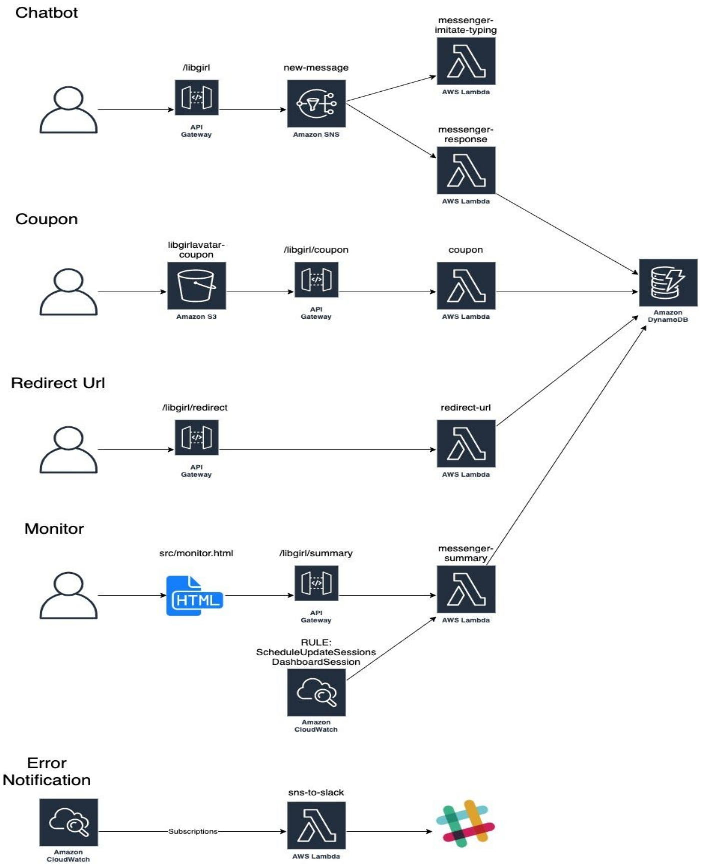
- Coupon: We give coupons to the users through conversations, and the coupon component manages with the redeeming processes. When a user is redeeming a coupon in a store, a link triggers the browser to go to the redeeming page, which is a simple HTML file hosted on s3. By entering the redeeming of the information, the lambda “coupon” communicates with the database (DynamoDB) to check the validity of the redeeming action and make redeeming records.

- Redirect URL: Our chatbot advertises some clients' website to the users. By the redirect URL components, we count the users' clicking of the links for charging the advertising clients.
- Monitor: Making the statistics & KPIs, e.g. total user counts, turns of conversations, retention, coupon redeeming counts, advertising links clicking counts, for our chatbot service for internal review.






- Error notification: send notifications to our team's slack when errors occur on the production chatbot.




Libgirl Bot Structure

## 2. Replying Mechanisms

The general replying method of the Libgirl Bot is based on AWS Elasticsearch since retrieval-based conversational AI is the baseline method (Yan, 2018). Through matching text to reply table in our database, Elasticsearch automatically matches the first 5 texts that are most similar to the input of the user, and randomly pick one of their value (response) to return.

We've also have designed some tiny utilities, such as giving domestic news, doing lucky draw (and the user might get a coupon), sending referring link for our cooperative companies (if the user expresses specific needs that meets the company's service)...etc.

We also provide a special mode that detects the user's emotional status. Once the user gets in a bad status that may harm him/herself, the Libgirl Bot would try to comfort him/her and would send a warning event to us and take the action to call 119 by us if it's necessary.

## 3. Conclusion and Outlook

For improving the performance of our chatbot, we are implementing neural network models to generate the reply text. The model is run on PyTorch (Python), and there are 2 main difficulties to deploy the neural network model:

- packaging the python dependencies, including the huge ones like PyTorch.
- load the huge neural network model (~532MB) when launching the service.

We'll apply our replying method using the model once our performance is good enough. Check Inner Voice for our developing neural network model.

The future goal is to let our Libgirl Bot learn to understand users' context and do targeted advertising or merchandise to them. See the below gif example.

## 4. Reference

Yan, R. (2018). "Chitty-Chitty-Chat Bot": Deep Learning for Conversational AI. *Www.Ijcai.Org*, 5520–5526. https://www.ijcai.org/Proceedings/2018/778

**Inner Voice - Training Methodology to Produce Machine Thinking and Reasoning**

**INTRODUCTION**

Why can people communicate with each other so easily, and not have to go into detail every time? How do I know if you can understand which color we said when we said ‘red’? Furthermore, the players on the field can even do some ‘complex communication’ without talking. Because we are sharing the similar concept in what we do.

The concept is what we know and how we do, but we don’t talk about it all the time. In the case, two strangers bump into each other. How will they interact? Basically, we can claim they would interact according to social value, and the social value is the concept we mentioned. Even though we are used to taking it as common sense, and do it like reflex actions, it will go wrong or will become a fight once unspoken-rules mismatch between two individuals.

When unspoken-rules pop up one-by-one in our mind, we say we are thinking or reasoning. Inner Voice is a traning methodology to realize machine producing unspoken-rules.

With Inner Voice, now the machine starts to think.

**METHOD**

We prepared data presentating the relationship between text and unspoken-rules. Methodology detail is at a further confidential level.

**CORE VALUE**

1. Multi-turn dialogue
2. Explanable AI
3. Easy to incorporate domain knowledge
4. Flexible and extensible compared to modifying either neural network model or programming source code

**Hebbian Digraph - Hebbian Rules with a Special Neural Network Structure for Self-Supervised Learning**

**INTRODUCTION**

Self-supervised learning is on the trend of artificial neural networks.
We induced Hebbian rules as the main weight updating rules in our developing model.

We think Hebbian rules are more native to self-supervised learning problems. Our model design also includes a special network structure to enhance context sensitivity with an interactive usage.

**METHOD**

The developing methodology detail is at a further confidential level.

**Core Value Postulation**

1. much reduce computing resource consumption
2. much smaller model size
3. context sensitive
4. no theoretical limitation on the size of context window
5. easier to do parallel computing

# Making Real AI Series

## Abstract

This is marketing oriented work. We’re publishing each deck of slides on the Internet to persuade the knowledgeable public that we know the most about how to make AGI.

# The Solution for Never-Ending Arguing on Definition of Intelligence

## The Solution for Never-Ending Arguing on Definition of Intelligence

Making Real AI - Series

(Shaka) Shih-Chia Chen

Founder/CEO
www.libgirl.com

## Definitions of Intelligence

“Intelligence has been defined in many ways: the capacity for logic, understanding, self-awareness, learning, emotional knowledge, reasoning, planning, creativity, critical thinking, and problem solving.”
- Intelligence, Wikipedia

People don’t have consensus on its definition.

## Definitions of Intelligence

**Diversity** is of the true essence of Intelligence.

Yet, there is some **mechanism behind** such diverse capabilities including capacity for logic, understanding, self-awareness, learning, emotional knowledge, reasoning, planning, creativity, critical thinking, problem solving, or more.

# Thesis

**It's impossible to give a reductionist definition to cover all diverse phenomena of intelligence.**

**Instead, we can build the foundations of intelligence that can manifest intelligence.**

## Problem of Reductionist Definition for Intelligence

The concept of intelligence covers too much, and it is vague.
It even covers cases that seem non-intelligence.

Learning is one trait of intelligence, but a subject can learn to be stupid.
Is it still intelligence?

Adaptation is one trait of intelligence, but a bacteria species can adapt well.
Are they intelligence?

## Problem of Reductionist Definition for Intelligence

Reductionist definition of intelligence can't handle above logical paradox without proposing other definitions.

People still won't have consensus on those further definitions.

## Solution - Foundations of Intelligence over Intelligence Itself

Diversity is of the true essence of Intelligence.

We can't define such diversity,
but we can have **foundations** of it.

That is,
with these **foundations** a being can, but doesn't have to,
grow to demonstrate all potential aspects of intelligence.

## The Foundations is Memory, Learning and Adaptation

"More generally, it can be described as the ability to perceive or infer information, and to retain it as knowledge to be applied towards adaptive behaviors within an environment or context."
- Intelligence, Wikipedia

It means memory, learning, and adaptation. With them, a subject has the potential to keep part of its state but also keep changing.

That's the foundations that a being can **manifest all diverse phenomena** of intelligence.

## The Foundations is Memory, Learning and Adaptation

"More generally, it can be described as the ability to perceive or infer information, and to retain it as knowledge to be applied towards adaptive behaviors within an environment or context."
- Intelligence, Wikipedia

Memory Learning Adaptation

Wikipedia's definition is right as long as it is for the foundations of intelligence instead of intelligence itself.

## Sum up

1. No reductionist definition of intelligence.
2. Reach consensus on foundations of intelligence.
3. Use the right word - say foundations of intelligence
4. Memory, learning, and adaptation should be (at least part of) the foundations of intelligence.

## Let’s Build the Foundations and Make Real AI

Follow Libgirl Co., Ltd. Facebook: https://www.facebook.com/libgirldotcom/

Intelligence is multi-disciplined.
To make real AI, we have been doing all things from philosophy, psychology, neuroscience, machine learning, engineering, product making, to business.

Let’s make real AI and its product to benefit all human beings.

# Appendix

## Non reductionist definition of intelligence

Intelligence is the ability to perform human-like Wittgensteinian language games. (Hsu, 2018)

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# Learning Context is All You Need for Task-general Artificial Intelligence

# Learning Context is All You Need for Task-General Artificial Intelligence

Making Real AI - Series

(Shaka) Shih-Chia Chen

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## Problems of Task-Specific AI/Machine Learning

- Task specific machine learning systems are brittle and sensitive to
  - Data distribution shifts
  - Task specification changes
- Such shifts and changes happen a lot in practical application developments and operations
  =>
  - Systems make mistakes
  - Manual tuning costs a lot

See appendix for more information

# Problems of Task-Specific AI/Machine Learning

- Task specific machine learning systems are brittle and sensitive to
  - Data distribution shifts
  - Task specification changes
- Such shifts and changes happen a lot in practical application developments and operations
  =>
  - Systems make mistakes
  - Manual tuning costs a lot

We need
task-general AI

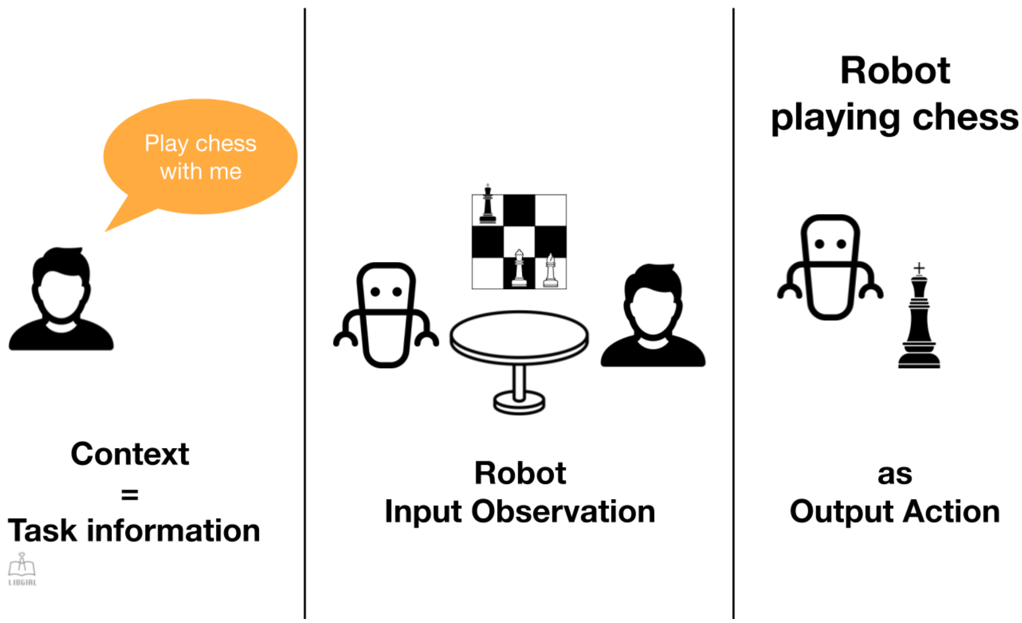
See appendix for more information

**Thesis:**

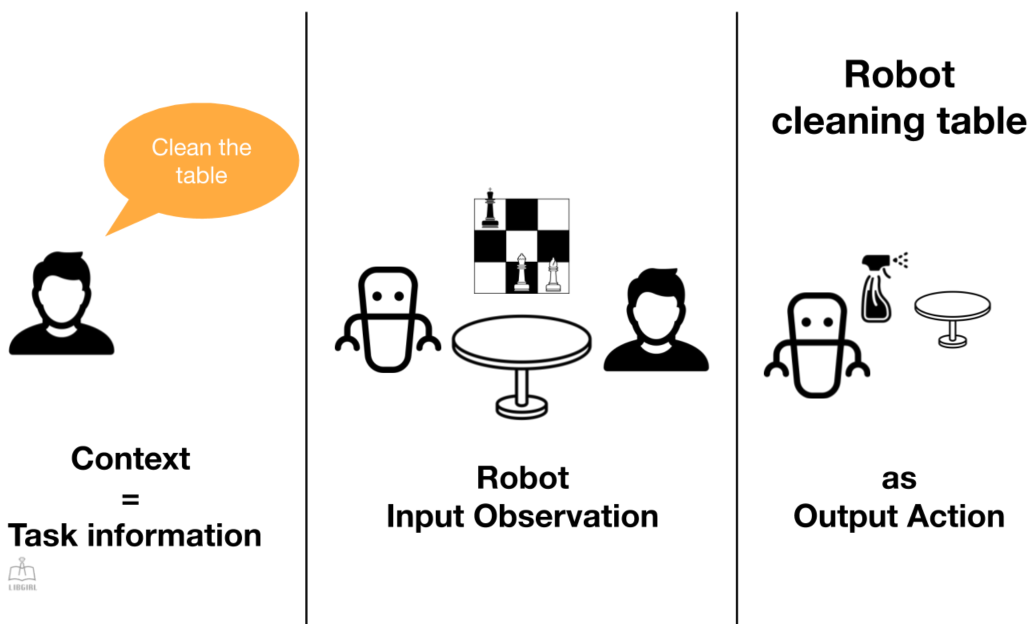
**Learning context is all you need for
task-general AI
=
As long as a single machine learning model can learn to distinguish
unbounded amount of contexts and give output accordingly,
the model is a task-general AI.**

**In some definition, a task-general AI is also an Artificial General Intelligence
(AGI)**

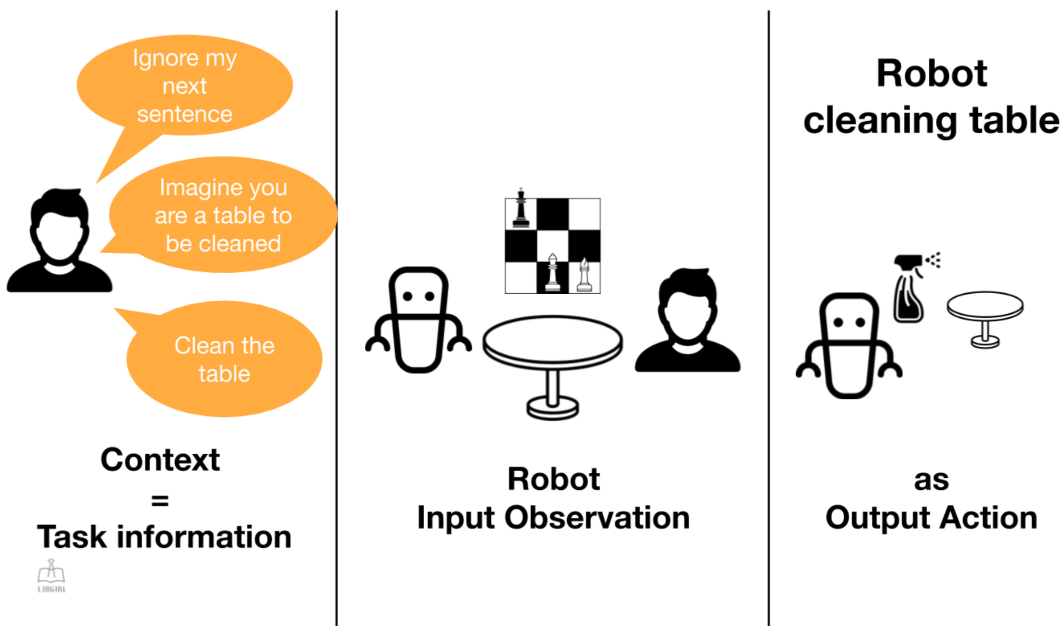
## Task-General = Context Sensitive



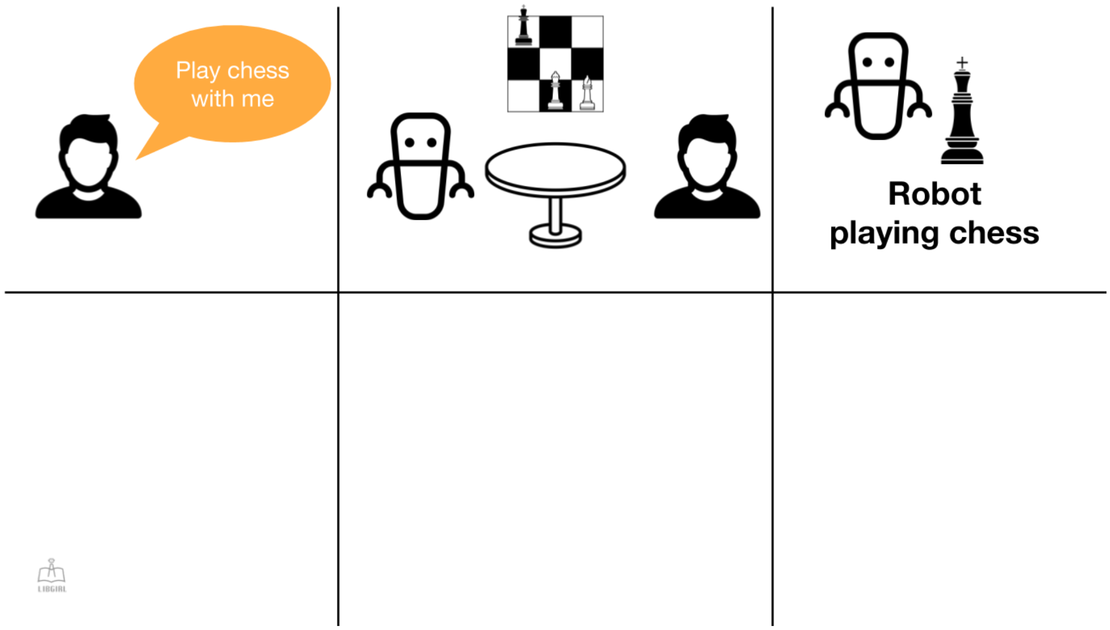

## Task-General = Context Sensitive



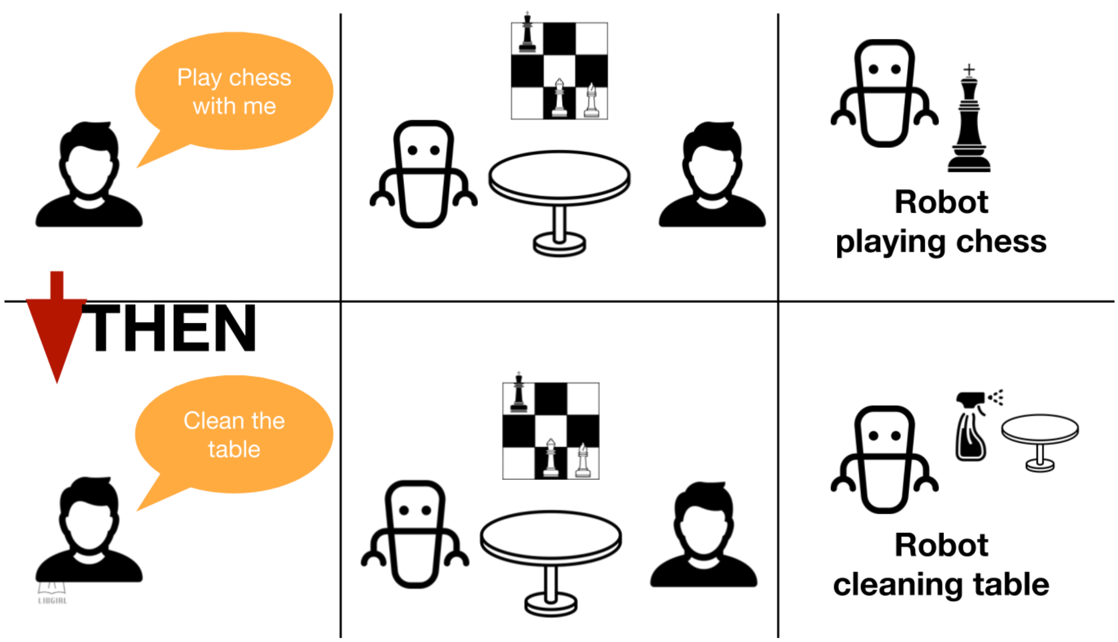
# Longer Historical Context = Higher Context Sensitivity



## Context Switch = Task Switch




## Context Switch = Task Switch



# Related Works

- Task-general machine learning trials based on their single context-sensitive models. (language tasks only)
    - OpenAI's GPT-2 (Radford & Wu, 2019)
    - National Taiwan University's LAMOL (Sun & Ho, 2019)

# Related Works

- Learning to distinguish unbounded amount of contexts.
  (long-range contextual dependencies)
  (longer-historical contexts)
    - Google's Reformer can learn the contextual relationship of sequences up to 1 million words.
      (Kitaev & Kaiser, 2020)
    - Dai & Yang (2019) proposed Transformer-XL, it can capture sequential dependencies beyond a fixed-length context.

# Let's Do

- Machine learning for learning context with longer spatiotemporal dependency.
- To train a single model with complicated contextual data, and then to demonstrate its stronger task-generality.
- Problems conquered

  - Data distribution shifts
  - Task specification changes

## Next

Follow our *Making Real AI* series

Let's further investigate the following terminologies:

Task-specific VS. Task-general

AI VS. AGI

In the next slides.

# Appendix

## Dataset Shift and Software Requirement Changes

"Machine learning systems now excel (in expectation) at tasks they are trained for by using a combination of large datasets, high-capacity models, and supervised learning (Krizhevsky et al., 2012) (Sutskever et al., 2014) (Amodei et al., 2016).
Yet these systems are brittle and sensitive to slight changes in the data distribution (Recht et al., 2018) and task specification (Kirkpatrick et al., 2017).
Current systems are better characterized as narrow experts rather than competent generalists."
(Radford & Wu, 2019)

# Dataset Shift and Software Requirement Changes

- Dataset shift is present in most practical applications (Quiñonero-Candela, 2009)

- "It is often more than 50% of the requirements are changed before the completion of a software project."
(Kotonya and Sommerville, 1998)

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# No Essential Difference Between AI and AGI

Making Real AI - Series

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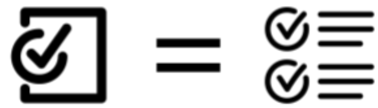
## Background - Task Specificity as the Main Distinguisher between Narrow AI and AGI

- "……training an algorithm on a dataset in **specialist areas**, for example. That's what we call **Narrow AI**……" (Baxter, 2019)
- " Artificial General Intelligence (AGI) can be defined as the ability of a machine to **perform any task** that a human can." (Joshi, 2019)
- "……create a general intelligence which can **solve multiple problems**." (Panchal, 2019)

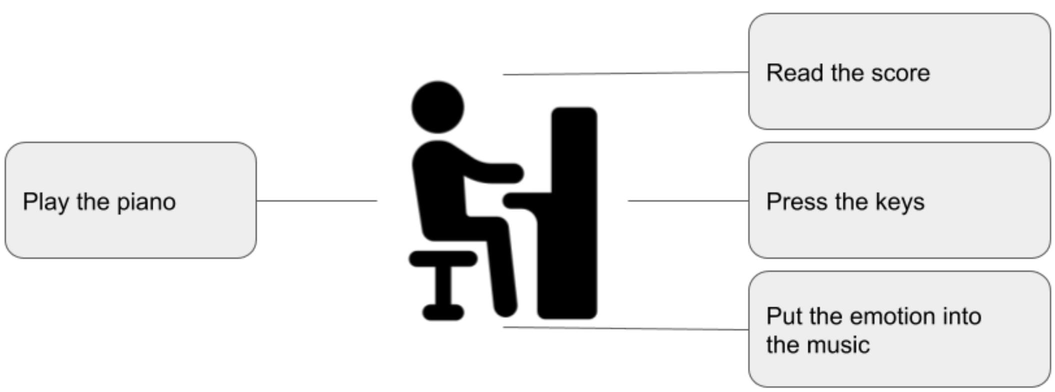
## Fact

There is no common standard to judge some activity is a single task or multiple tasks.



Taking specific action according to specific context is all you need. (Chen, 2020)

## Playing Piano is Single Task AND Multiple Tasks



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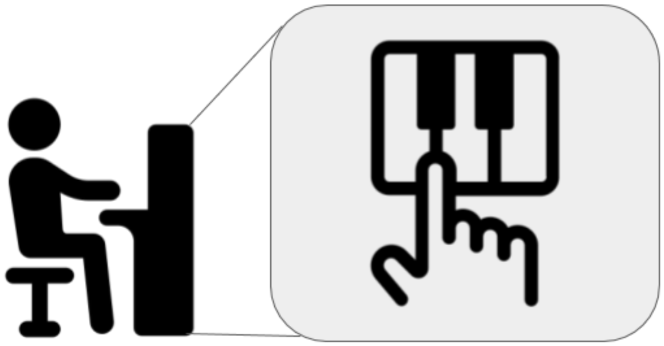
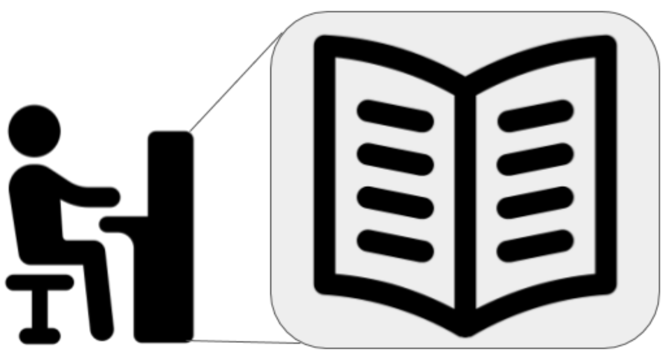


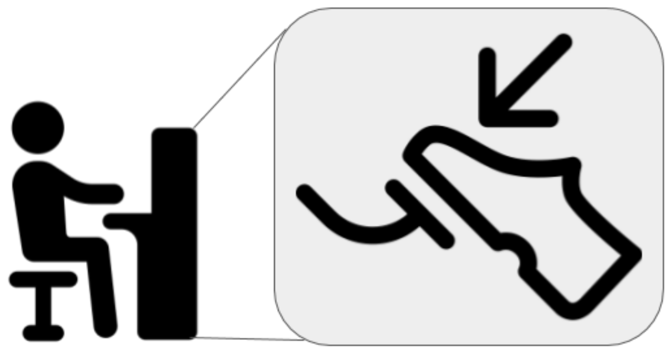
Pressing keys at some moment

## Playing Piano is Single Task AND Multiple Tasks



Flip the score at some next moment

## Playing Piano is Single Task AND Multiple Tasks



Press the pedal sometimes

## Being a Pianist Includes More Tasks

 Performance etiquette

 Cut nails often

 Decide what concerts to participate

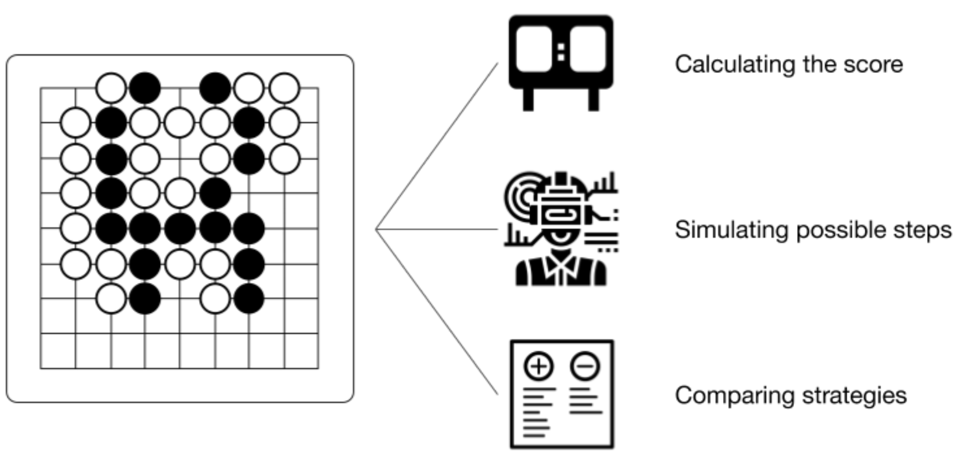
 Dresses

• • • • • •

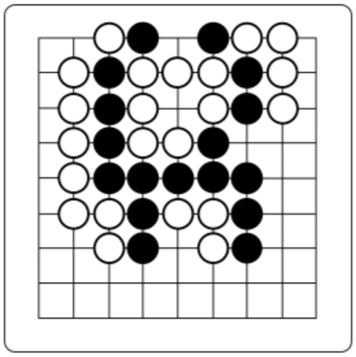
And more……

## Life is Single YET Multiple Tasks


## Even Playing Go is Single YET Multiple Tasks



## Even Playing Go is Context Sensitive



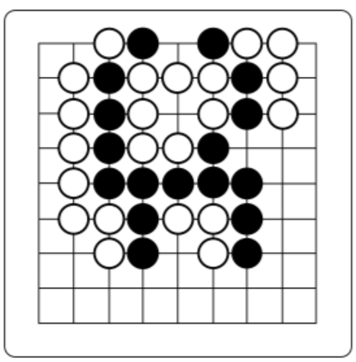
Do step simulation when

computation resources are enough

and

still have time.

## Even Playing Go is Context Sensitive



Compare and make a decision when

computation resources are limited

and

little time left.

## Let’s Do

1. Stop the discrimination between AI and AGI.
2. We can still use the term task-specific or task-general, but they are relative terms without a common decisive standard.
3. Learning context is all you need for more powerful AI.
(Chen, 2020)

Also Please Follow our *Making Real AI* series

And welcome any collaboration

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