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Social Interactions for Autonomous Driving: A Review and Perspectives

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Contents

Social Interactions for Autonomous Driving: A Review and Perspectives

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ABSTRACT

No human drives a car in a vacuum; she/he must negotiate with other road users to achieve their goals in social traffic scenes. A rational human driver can interact with other road users in a socially-compatible way through implicit communications to complete their driving tasks smoothly in interaction-intensive, safety-critical environments. This monograph aims to review the existing approaches and theories to help understand and rethink the interactions among human drivers toward social autonomous driving. We take this survey to seek the answers to a series of fundamental questions: 1) What is social interaction in road traffic scenes? 2) How to measure and evaluate social interaction? 3) How to model and reveal the process of social interaction? 4) How do human drivers reach an implicit agreement and negotiate smoothly in social interaction? This monograph reviews various approaches to modeling and learning the

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social interactions between human drivers, ranging from optimization theory, deep learning, and graphical models to social force theory and behavioral & cognitive science. We also highlight some new directions, critical challenges, and opening questions for future research.

1

Introduction

1.1 Background

Humans can be trained to be remarkable drivers with powerful capabilities in social interaction. In real-world traffic, rational human drivers can make socially-compatible decisions in complex and crowded scenarios by efficiently negotiating with their surroundings using non-linguistic communications such as gesturing (e.g., waving hands to the other car to give way), deictics (e.g., using turn signals to indicate intentions), and motion cues (e.g., accelerating/decelerating/turning) (Kauffmann *et al.*, 2018). Understanding the principles and rules of the dynamic interaction among human drivers in complex traffic scenes allows 1) generating diverse social driving behaviors that leverage beliefs and expectations about others' actions or reactions; 2) predicting the future states of a scene with moving objects, which is essential to building probably safe intelligent vehicles with the capabilities of behavior prediction (Wang *et al.*, 2021d; Anderson *et al.*, 2020) and potential collision detection (Roy *et al.*, 2022); and 3) creating realistic driving simulators (Luo *et al.*, 2019). However, this task is not trivial since various social factors exist along the driving interaction process, including social motivation[1], social perception[2], and social control[3], from the perspective of traffic psychologists (Zajonc, 1966; Wilde, 1980). Generally, human driving behavior is compounded by human drivers' **social interactions** and their **physical interactions** with the scene.

- **Social Interactions.** When driving on the road, humans often interact with other surrounding drivers *socially* via implicit and/or explicit communications. For example, a courteous driver (denoted as driver A) on the main road would actively give way to another vehicle merging at highway on-ramps (denoted as driver B) to avoid potential conflicts, and interactively, driver B can understand driver A's intentions.
- **Physical Interactions.** Human driving behaviors depend not only on other human agents around them but also on the physical traffic scenes. This includes the static physical obstacles (e.g., parked vehicles, road boundaries) and dynamic physical cues (e.g., traffic lights and signs), which may influence human drivers' decisions and movements during interactions.

Social interactions are more intricate than physical interactions due to the continuous closed-loop feedback among human agents, and many uncertainties exist. The social interaction may only require **simple** decision-making, which directly maps human perceptions to actions without specific reasoning and planning (e.g., stimulus-response, reactive interaction, car-following). The social interaction may also require **complex** decision making, forcing human drivers to cautiously decide an action among alternatives (e.g., yield or pass) by predicting other

[1]Social motivations are the factors that drive people to take action to interact with other people. Unlike motivation, which emphasizes the reasons or desires to do some actions, social motivation often requires interaction with other human agents.

[2]The social perception here refers to the processes by which a person uses the behavior of others to understand or reason about those individuals, particularly regarding their motives, attitudes, or values. Unlike object perception, social perception often involves sophisticated *inferences* which go far beyond the data observed.

[3]Social control refers to sets of rules and standards that bound individuals to specific pressures, thus maintaining conformity to established norms (Spillman, 2012).

agents' behaviors and evaluating the influence of all possible alternatives (Johora and Müller, 2018). On the other hand, human drivers can interact with each other via explicit communications, such as using hand gestures and flashing lights. However, explicit communication options are not always available or the most efficient in practice. In many cases, human drivers prefer to use implicit rather than explicit communications to complete their driving tasks in interactive traffic scenarios (Lee *et al.*, 2021). Therefore, this tutorial will mainly discuss the **complex, implicit social interactions** among human drivers in measurement approaches, modeling methods, and potential challenges.

1.2 Definitions of Social Interactions in Road Traffic

1.2.1 Interactions in Road Traffic

What is interaction? Interaction is a common term that can have many definitions in different disciplines. In the context of transportation, Markkula *et al.* (2020) proposed a unified definition of interaction among all types of road users. In this survey, we follow this unified definition to describe **inter-vehicle interactions** as

> '*A situation where the behavior of at least two road users can be interpreted as being influenced by the possibility that they are both intending to occupy the same region of space at the same time in the near future.*'

This definition provides clear criteria for recognizing whether a traffic scenario is interactive. This definition implies that interaction should consist of at least three fundamental elements: (i) there are two or more agents involved, (ii) these agents are influencing each other, and (iii) there are potential spatiotemporal conflicts among agents. For example, two human drivers on different road arms at a *signalized* urban intersection usually do NOT influence each other. The two drivers should not be recognized as interactive since the traffic light regulartes their behaviors: one passes first with green light, and the other keeps static with red light.

1.2.2 Social Interactions in Road Traffic

What is social interaction? Social interaction has various definitions across psychology, behavioral science, and robotics. In general, social interaction is a behavior that tries to affect or account for each other's *subjective experiences*[4] or *intentions* (Duvall, 1979). In road traffic conditions, the definition of interactions among vehicles in Section 1.2.1 proposed by Markkula *et al.* (2020) provides information about *who* will be involved and *when* interaction will occur. However, this definition cannot interpret the underlying dynamic process of interactions, such as *how* one agent should consider the effects of other agents' actions and reactions. Toward this point, traffic psychologists (Wilde, 1976; Wilde, 1980) conceptually hold that the social interaction process in natural traffic possesses certain characteristics such as the tendencies of social habits and values, social expectations, and social interaction patterns. In this monograph we provide a quantifiable definition of **social interaction in road traffic** as:

> *' ... a dynamic sequence of acts that mutually consider the actions and reactions of individuals through an information exchange process between two or more agents to maximize benefits and minimize costs.'*

In this way, social interaction possesses the three essential attributes corresponding to: **Dynamics** (closed-loop feedback among multiple agents), **measurement** (information exchange), and **decision** (utility maximization).

- **Dynamics.** Every road user considers its neighbors' actions and future reactions to social traffic, forming a continuous multi-agent closed-loop feedback system. In this system, every road user contributes to the aggregated dynamics of the traffic system and is affected by the aggregated dynamics.

- **Measurement.** Road users may have different social driving characteristics (e.g., intentions, driving styles, driving preferences),

[4] A subjective experience is produced by the individual human mind and refers to the emotional and cognitive impact of a human experience (LeDoux and Hofmann, 2018).

leading to various actions and reactions. For efficient and safe social interaction, every road user needs to deliver their social cues and identify others' social cues, forming an information exchange process.

- **Decision.** Based on the dynamics and measurement, human drivers involved in the interaction are rationally seeking to maximize their utility.

Such a unified definition of social interaction provides a computational framework that connects the fields of psychology and robotics.

1.3 From Inter-Human to Human-AV Interactions

Inter-Human Social Interactions Humans are natural social communicators; human drivers negotiate with other agents safely and efficiently, forming an interaction-intensive and multi-agent system. In general, human driving behaviors are dominated by two types of norms: legal and social. Traffic rules form the legal norms, and humans' social factors form the social norms. In real traffic, human drivers do not always act with formal behaviors (i.e., legal norms) by strictly and stereotypedly following traffic laws (e.g., keeping under the speed limit on highways). On the contrary, human drivers will usually drive according to implicit social norms and rules that facilitate efficient and safe behavior on the road (Müller *et al.*, 2016). Existing research also reveals that acting according to the informal behaviors (i.e., social norms) can make behavior recognizable and predictable for other human agents, thus decreasing the interaction uncertainty and facilitating every agent's decision-making (Wilde, 1980; Havârneanu and Havârneanu, 2012). As a result, understanding and inferring other humans' driving behaviors by pure legal norms might be ineffective because:

- **Traffic rules do not always specify driving behavior.** For example, when a driver intends to change lanes in congested traffic, the traffic laws only forbid collisions but do not specifically describe how the driver should cooperate or compete with others to create gaps. Social norms usually dominate such interaction behaviors.

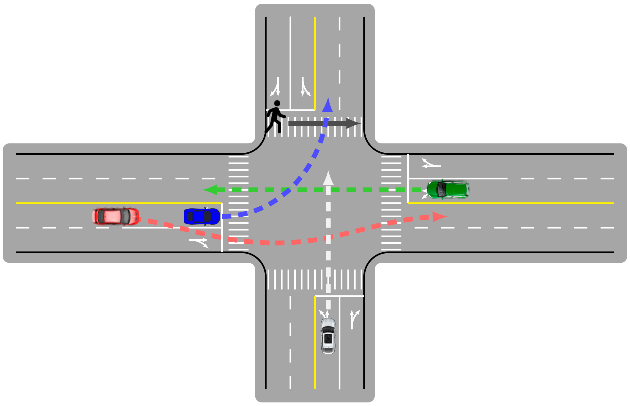

Figure 1.1: An example of interaction among human agents in uncontrolled traffic scenarios. The leading vehicle (blue) is yielding to the upcoming vehicle (green) and the pedestrian (black) crossing the road.

- **Human drivers do not strictly obey traffic rules.** Figure 1.1 illustrates an intersection scenario that frequently occurs in real life. An experienced driver (red) intends to pass the intersection, but its leading vehicle is waiting to turn left. The driver could overtake the leading vehicle by crossing the solid white line and passing through from the right side to save travel time. Though slightly violating the traffic rules, such behaviors improve traffic flow efficiency.

Hence, equipping Autonomous Vehicles (AVs) with an understanding of the collective dynamics of human-human interactions may allow them to make informed and socially compatible decisions in human environments.

Social Behaviors for Autonomous Vehicles As moving intelligence-embodied agents, autonomous vehicles also need to interact with human agents and will become part of a complex socio-technical system (Müller *et al.*, 2016). In such a safety-critical system, AVs should blend seamlessly into roads populated with human drivers and be socially compatible with reaching human-level interaction performance. However, a big gap exists between norms followed by human drivers and autonomous vehicles, as

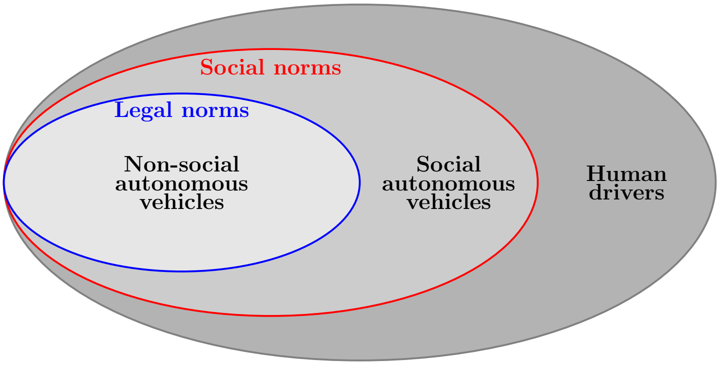

Figure 1.2: Illustration of the differences between human drivers, social autonomous vehicles, and non-social autonomous vehicles from the perspective of social and legal norms.

illustrated by Figure 1.2. Autonomous vehicles strictly following legal norms might be unable to deal with highly-interactive scenarios and confuse other human drivers following the social norms. For example, an AV strictly and stereotypedly follows the 3-second law before a stop sign (could be viewed as the *legal norms*) would deliver confusing social cues to other human agents: 'Why the vehicle does not move ahead?' To communicate effectively and efficiently, AVs will need to mimic, or ideally improve upon, human-like driving, which requires them to:

- **Understand and adapt others' social and motion cues**[5]**.** This treats AVs as information receivers, which keeps *themselves* functionally safe and efficient. For example, failing to recognize the aggressiveness level of other drivers would make the AV unsafe or too conservative.

- **Deliver recognizable, informative social and motion cues.** This treats AVs as information senders, making AVs' behaviors perceivable and understandable to *other human drivers*, allowing them to make safe and efficient maneuvers. For example, an AV hesitating between yield and pass would confuse other road users, resulting in accidents or traffic jams.

[5]Social cues refer to the clues to social characteristics, such as intention, driving styles, driving preferences, etc.

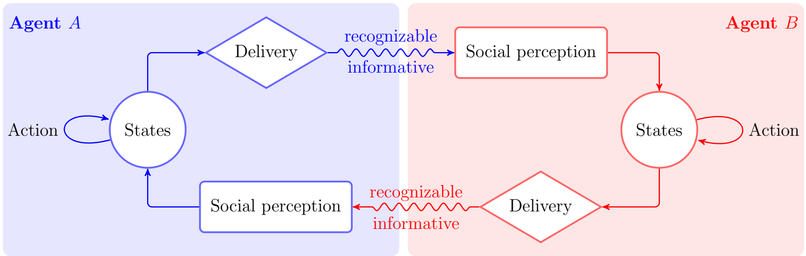

Figure 1.3: Illustration of the closed-loop formalism of interaction between two agents (Agents A and B), which also generalizes to multi-agent systems.

It should be emphasized that we are *not* claiming that AVs should violate traffic regulation in order to behave like a human driver or be socially compatible. We believe that learning and understanding the social norms followed by human drivers could benefit efficient and safe interactions.

Figure 1.3 illustrates the dynamic communication procedure between two agents (human drivers and/or AVs), each of which plays two roles in the information exchange process: information *sender* and *receiver*. For instance, Agent A would act as an information sender to 'tell' Agent B about its intents. Meanwhile, Agent B should perceive and understand the information delivered by Agent A (i.e., perception) and then take some actions to respond or adapt to Agent A by delivering recognizable and helpful information.

Endowing AVs with the human social capability to enhance interaction performance in complex traffic scenarios has shown significant progress. For example, human social preferences (e.g., altruistic, prosocial, egoistic, and competitive) and the levels of cooperation while interacting with an AV are quantitatively evaluated using computational cognitive models (Müller *et al.*, 2016; Toghi *et al.*, 2021b; Toghi *et al.*, 2021a).

1.4 Scope and Framework of the Monograph

This monograph aims to comprehensively review the interactions among on-road vehicles (human-driven vehicles and/or AVs) toward socially-compatible self-driving cars. The interactions with other types of road users (e.g., pedestrians and cyclists) are out of the scope of this paper. We suggest readers refer to other literature reviews for autonomous vehicle-pedestrian interactions (Rasouli and Tsotsos, 2019), driver-cyclist interactions (Rubie *et al.*, 2020; Bella and Silvestri, 2017), and pedestrian-pedestrian interactions (Rudenko *et al.*, 2020).

Few literature reviews exist on the interactions between human drivers except Mozaffari *et al.* (2022), Di and Shi (2021), and Gilles *et al.* (2022), which are all limited to AI-guided learning approaches or specific behavior prediction tasks. However, existing works present many approaches to modeling interactions far beyond the content reviewed in Mozaffari *et al.* (2022) and Gilles *et al.* (2022). Although literature review of Di and Shi (2021) tabled and summarized some existing works, they did not provide the behind ideas and principles of approaches to modeling interaction among drivers. To bridge the gap, we will review a wide variety of state-of-the-art works with keywords ‘social-aware decision-making’, ‘interaction-aware’, ‘cooperative decision/policy’, ‘multi-vehicle interactions’ in the ground vehicles and transportation, robotics, and their references and citations. The related approaches range from optimization theory, deep learning, and graph-based models to social fields and behavioral and cognitive sciences.

Section 2 discusses the essential definitions and basic ideas of social interactions in road traffic. Section 3 discusses the approaches to modeling and learning social interactions among human drivers. Section 4 provides some new directions, critical challenges, and opening questions for future, followed by conclusions in Section 5.

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Appendices

A

Markov Decision Processes and Markov Games

Section 3.1.2 discusses some works that utilize various game-theoretical frameworks to formulate the interaction among agents; each agent can be modeled by employing a Markov decision process (MDP). In what follows, we will briefly revisit MDPs and Markov games.

Definition A.1 (Markov Decision Processes)**.** An MDP can be described by a tuple of key elements, $\langle s, a, p, r, \gamma \rangle$ with

- $s \in \mathcal{S}$ — The environment states in the state space $\mathcal{S}$.
- $a \in \mathcal{A}$ — Agent's possible actions in the action space $\mathcal{A}$.
- $p : \mathcal{S} \times \mathcal{A} \to \mathcal{S}$ — For each time step $t > 0$, given an agent's action $a \in \mathcal{A}$, the transition probability from a state $s \in \mathcal{S}$ to the state $s' \in \mathcal{S}$ in the next time step.
- $r : \mathcal{S} \times \mathcal{A} \times \mathcal{S} \to \mathbb{R}$ — The reward function that returns a scalar value (i.e., $r \in \mathbb{R}$) to the agent for a state transition from s to s' after taking an action a.
- $\gamma \in [0, 1]$ — The discount factor that represents the value of time.

Definition A.2 (Markov Games or Stochastic Games)**.** A stochastic game can be viewed as a multiplayer extension to the Markov decision process, constituted of a set of key elements $\langle N, s, \{a_i\}_{i=1}^{N}, P, \{r_i\}_{i=1}^{N}, \gamma \rangle$, with

- $N \in \mathbb{N}^+$ — The number of agents.
- $s \in \mathcal{S}$ — The environment states shared by all agents, over the state space $\mathcal{S}$.

- $a_i \in \mathcal{A}_i$ — The i-th agent's action in its action space $\mathcal{A}_i$.
- $p : \mathcal{S} \times \mathcal{A}_1 \times \mathcal{A}_2 \times \cdots \times \mathcal{A}_N \to \mathcal{S}$ — For each time step, given agents' joint actions $\boldsymbol{a} = [a_1, a_2, \ldots, a_N]$, the transition probability from state $s \in \mathcal{S}$ to state $s' \in \mathcal{S}$ in the next time step.
- $r_i : \mathcal{S} \times \{\mathcal{A}_i\}_{i=1}^N \times \mathcal{S}$ — The reward function that returns a scalar value to the i-th agent for a transition from $(s, \boldsymbol{a})$ to s'.
- γ — The discount factor that represents the value of time.

Each agent i aims to maximize its expected discounted total rewards with the starting state s_0 at time t

$$V_{\pi_i}(s) = \mathbb{E}\left[\sum_{\tau=0} \gamma^\tau r_i^{\tau+t} | s_t = s_0\right]. \tag{A.1}$$

B

Graph Models

Definition B.1 (Graph/Digraph). A graph $\mathbf{G}$ is a pair $(\mathcal{V}, \mathcal{E})$, where $\mathcal{V}$ is a finite set of vertices, and $\mathcal{E}$ is a set of edges. If each edge is an *ordered* pair (u, v) of nodes with $(u, v) \in \mathcal{V} \times \mathcal{V}$, $u \neq v$, the graph is called digraph.

Definition B.2 (Node Network). A node network (or node weighted graph) is a triple of $(\mathcal{V}, \mathcal{E}, f)$, where f is a function mapping *vertices* to numbers, $f : \mathcal{V} \to \mathcal{N}$, where $\mathcal{N}$ is some number system, assigning a value (or weight) which may be real (or complex) numbers.

Definition B.3 (Edge network). A edge network (or edge weighted graph) is a is a triple $(\mathcal{V}, \mathcal{E}, g)$, where g is a function mapping *edges* to numbers.

In general, a graph or network consists of the following entities: a set of vertices $\mathcal{V}$, a set of edges $\mathcal{E}$, a function mapping vertices to numbers f, a function mapping edges to numbers g. A *dynamic graph* is obtained when any of these four entities changes over time (Harary and Gupta, 1997).

Definition B.4 (Edge network). A edge network (or edge weighted graph) is a is a triple $(\mathcal{V}, \mathcal{E}, g)$, where g is a function mapping *edges* to numbers.

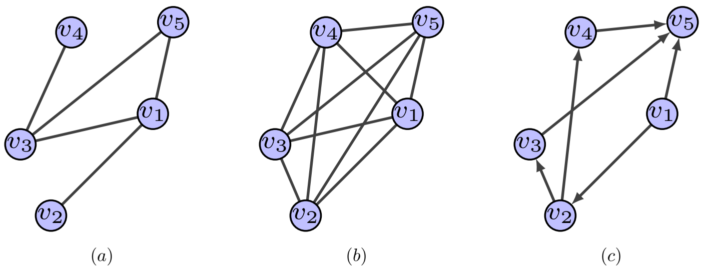


Figure B.1: Examples of three types of graphs with five nodes. (a) incomplete undirected graph, (b) complete graph (or fully connected graph), and (c) directed graph.

Definition B.5 (Adjacency, degree, and Laplacian matrices)**.** Figure B.1(a) represents an undirected graph with five nodes $v_1 \sim v_5$ and five edges (v_1, v_2), (v_1, v_3), (v_1, v_5), (v_3, v_4), and (v_3, v_5). The adjacency ($\mathbf{A}$), degree ($\mathbf{D}$), and Laplacian ($\mathbf{L} = \mathbf{D} - \mathbf{A}$) matrices for the graph is

$$\mathbf{A} = \begin{bmatrix} 0 & 1 & 1 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 1 \\ 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 \end{bmatrix},$$
$$\mathbf{D} = \begin{bmatrix} 3 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 3 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 2 \end{bmatrix}, \tag{B.1}$$
$$\mathbf{L} = \begin{bmatrix} r3 & -1 & -1 & 0 & -1 \\ -1 & 1 & 0 & 0 & 0 \\ -1 & 0 & 3 & -1 & -1 \\ 0 & 0 & -1 & 1 & 0 \\ -1 & 0 & -1 & 0 & 2 \end{bmatrix}.$$

Of course, the entries of the adjacency matrix $\mathbf{A} = \{a_{i,j}\}$ can be the measurement (i.e., a real value as a weight, formed a weighted matrix) of the interaction intensity over time, for example, by assigning the entries $a_{i,j}^{(t)}$ at the time frame t as a function of the relative distance between two vehicles i and j (Cao *et al.*, 2021)

$$a_{i,j}^{(t)} = \begin{cases} 1/||\tau_t^i - \tau_t^j||_2, & i \neq j, \\ 0, & \text{otherwise.} \end{cases} \tag{B.2}$$

where τ_t^i and τ_t^j are the positions of agents i and j at time t. The introduced matrices (**A**, **D**, and **L**) allow us to capture the interactions between human drivers under a graph structure.

C

Attention Measure

Assume that individual human agent's behavioral information (or observed data) can be sufficiently encoded in a compact manner such as into a low-dimensional vector, denoted as $\boldsymbol{h}$, thus the relationship or influence between any two agents with corresponding vectorized entries ($\boldsymbol{h}_i \in \mathbb{R}^d$ for agent i and $\boldsymbol{h}_j \in \mathbb{R}^d$ for agent j) can be quantified by a function f

$$\alpha_{i,j} = f(\boldsymbol{h}_i, \boldsymbol{h}_j)$$

Generally, there are five frequently used quantification measures, and all of them are basically based on the operations on the *projections* of the vectors $\boldsymbol{h}_i$ and $\boldsymbol{h}_j$, i.e., dot production mathematically.

C.1 Content-based Attention

The idea of content-based attention is to quantify the similarity level using the cosine similarity by projecting one attention vector to the other one (Graves *et al.*, 2014):

$$f(\boldsymbol{h}_i, \boldsymbol{h}_j) = \cos(\boldsymbol{h}_i, \boldsymbol{h}_j) = \frac{\boldsymbol{h}_i^\top \boldsymbol{h}_j}{\parallel \boldsymbol{h}_i \parallel \parallel \boldsymbol{h}_i \parallel} = \frac{\boldsymbol{h}_i^\top}{\parallel \boldsymbol{h}_i \parallel} \frac{\boldsymbol{h}_j}{\parallel \boldsymbol{h}_j \parallel} \tag{C.1}$$

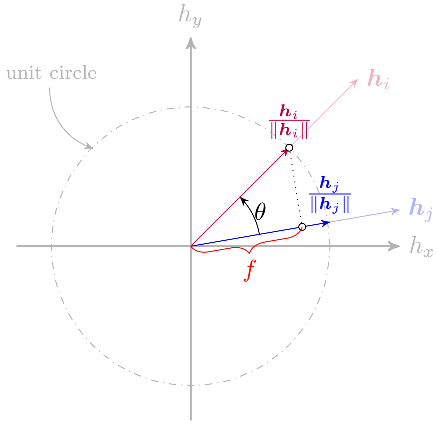


Figure C.1: Illustration of content-based attention with $\boldsymbol{h}_i$, $\boldsymbol{h}_j$ in a 2D plane.

The resulting similarity values $f \in [-1, 1]$ with interpretation: -1 indicates exactly opposite, and 1 indicates exactly the same, and 0 indicates decorrelation, while in-between values indicate intermediate similarity or dissimilarity. Figure C.1 geometrically visualizes the resulting values of the content-based attention, where θ denotes the angle between two vectors $\boldsymbol{h}_i$ and $\boldsymbol{h}_j$.

C.2 Concatenation Attention

The idea of concatenation attention is projecting the normalized weighted summation of two hidden vectors $\boldsymbol{h}_i$ and $\boldsymbol{h}_j$ to a defined value $\mathbf{v}_a$ (Bahdanau *et al.*, 2014):

$$f(\boldsymbol{h}_i, \boldsymbol{h}_j) = \mathbf{v}_a^\top \tanh\left(\mathbf{W}_a[\boldsymbol{h}_i \oplus \boldsymbol{h}_j]\right) \tag{C.2}$$

where $[\boldsymbol{h}_i \oplus \boldsymbol{h}_j]$ is the concatenation operation[1] and $\mathbf{W}_a$ is a weight matrix that projects the concatenated vector to a different vector.

On the other hand, the projection of concatenation of two vectors in (C.2) have an equivlent form as

[1]In Luong's (Luong *et al.*, 2015) and Bahdanau's (Bahdanau *et al.*, 2014) notations, they used a semicolon operator in the formulas to denote concatenation, i.e., $[\boldsymbol{h}_i; \boldsymbol{h}_j]$.

$$\mathbf{W}_a[\boldsymbol{h}_i \oplus \boldsymbol{h}_j] = \begin{bmatrix}\mathbf{W}_{a,i} & \mathbf{W}_{a,j}\end{bmatrix} \begin{bmatrix}\boldsymbol{h}_i \\ \boldsymbol{h}_j\end{bmatrix} = \mathbf{W}_{a,i}\boldsymbol{h}_i + \mathbf{W}_{a,j}\boldsymbol{h}_j \tag{C.3}$$

where $\mathbf{W}_a = [\mathbf{W}_{a,i} \oplus \mathbf{W}_{a,j}]$. The above equation directly follows from the definition of matrix multiplication. Therefore, the concatenation attention can also be presented in an equivalent form as

$$f(\boldsymbol{h}_i, \boldsymbol{h}_j) = \mathbf{v}_a^\top \tanh\left(\mathbf{W}_{a,i}\boldsymbol{h}_i + \mathbf{W}_{a,j}\boldsymbol{h}_j\right) \tag{C.4}$$

C.3 General Attention

The idea of general attention is straightforward proposed by Luong *et al.* (2015),

$$f(\boldsymbol{h}_i, \boldsymbol{h}_j) = \boldsymbol{h}_i^\top \mathbf{W}_a \boldsymbol{h}_j \tag{C.5}$$

which can be viewed as the projection of a linear transformation of one vector $\boldsymbol{h}_i$ over matrix $\mathbf{W}_a$ to another vector $\boldsymbol{h}_j$. More specifically, we have follows

$$\begin{aligned}
\boldsymbol{h}_i^\top \mathbf{W}_a \boldsymbol{h}_j &= \begin{bmatrix} h_{i1} & h_{i2} & \dots & h_{id} \end{bmatrix} \begin{bmatrix} w_{11} & w_{12} & \dots & w_{1d} \\ w_{21} & w_{22} & \dots & w_{2d} \\ \vdots & \vdots & \ddots & \vdots \\ w_{d1} & w_{d2} & \dots & w_{dd} \end{bmatrix} \begin{bmatrix} h_{j1} \\ h_{j2} \\ \vdots \\ h_{jd} \end{bmatrix} \\
&= \underbrace{\begin{bmatrix} \sum_{\ell=1}^d h_{i\ell} w_{\ell 1} & \sum_{\ell=1}^d h_{i\ell} w_{\ell 2} & \dots & \sum_{\ell=1}^d h_{i\ell} w_{\ell d} \end{bmatrix}}_{\text{Linear transformation of } \boldsymbol{h}_i} \begin{bmatrix} h_{j1} \\ h_{j2} \\ \vdots \\ h_{jd} \end{bmatrix} \\
&= \sum_{k=1}^d \sum_{\ell=1}^d h_{i\ell} w_{\ell k} h_{jk}
\end{aligned}$$

C.4 (Scale) Dot-Product Attention

Dot-product The dot-product attention (Luong *et al.*, 2015) is more implementation-friendly and can be viewed as a special case of the general attention with the transformation matrix $\mathbf{W}_a$ as an identity matrix, i.e., $\mathbf{W}_a = \mathbf{I}_{d\times d}$, obtaining

$$f(\boldsymbol{h}_i, \boldsymbol{h}_j) = \boldsymbol{h}_i^\top \boldsymbol{h}_j \tag{C.6}$$

Scaled Dot-product The scaled dot-product (Vaswani *et al.*, 2017) is a variant of the dot-product attention with an additional scaling factor $\frac{1}{\sqrt{d}}$

$$f(\boldsymbol{h}_i, \boldsymbol{h}_j) = \frac{\boldsymbol{h}_i^\top \boldsymbol{h}_j}{\sqrt{d}} \tag{C.7}$$

For a small value of d, (C.7) performs similarly with the dot-product attention but will outperform (C.6) for a large value of d when feeding into a softmax function.

C.5 (Embedded) Gaussian Attention

Gaussian The Gaussian-based attention is operating the dot-product over a Gaussian function (Wang *et al.*, 2018)

$$f(\boldsymbol{h}_i, \boldsymbol{h}_j) = e^{\boldsymbol{h}_i^\top \boldsymbol{h}_j} \tag{C.8}$$

Embedded Gaussian A simple extension of the Gaussian function is to compute the similarity in an *embedding space*, for example

$$f(\boldsymbol{h}_i, \boldsymbol{h}_j) = e^{\theta(\boldsymbol{h}_i)^\top \phi(\boldsymbol{h}_j)} \tag{C.9}$$

where $\theta(\cdot)$ and $\phi(\cdot)$ are embeddings. for example, linear transformations

$$\theta(\boldsymbol{h}_i) = \mathbf{W}_\theta \boldsymbol{h}_i \tag{C.10a}$$

$$\phi(\boldsymbol{h}_j) = \mathbf{W}_\phi \boldsymbol{h}_j \tag{C.10b}$$

Note that the embedded Gaussian attention can be viewed as re-shaping the similarity of the general attention over a Gaussian function since

$$e^{\theta(\boldsymbol{h}_i)^\top \phi(\boldsymbol{h}_j)} = e^{(\mathbf{W}_\theta \boldsymbol{h}_i)^\top \mathbf{W}_\phi \boldsymbol{h}_j} = e^{\boldsymbol{h}_i^\top \mathbf{W}_\theta^\top \mathbf{W}_\phi \boldsymbol{h}_j} = e^{\boldsymbol{h}_i^\top \mathbf{W}_a \boldsymbol{h}_j} \tag{C.11}$$

with $\mathbf{W}_a = \mathbf{W}_\theta^\top \mathbf{W}_\phi$.

D

Topological Braids

D.1 Braids

Braids are topological objects with algebraic and geometric presentations, which is usually denoted by the Cartesian coordinates (x, y, z) of a Euclidean space $\mathbb{R}^2 \times I$. A **braid string** is a curve

$$\begin{aligned} \mathsf{Br}(z) : I &\to \mathbb{R}^2 \\ z &\to x \times y \end{aligned} \tag{D.1}$$

that increases monotonically in z, for example, z could be time $t \in [0, \infty)$. That is, a braid string has exactly one point of intersection $\mathsf{Br}(z) = (x, y)$ with each plane $z \in I$.

A **braid on n-strings** or n-braids is a set of n strings $\mathsf{Br}_i(z)$, $i \in \{1, 2, \ldots, n\}$, i.e., $\mathcal{B}(z) = \{\mathsf{Br}_i(z)\}$, for which some properties hold:

(i) $\mathsf{Br}_i(z) \neq \mathsf{Br}_j(z)$ for $i \neq j$, $\forall z \in \mathbb{R}$;

(ii) $\mathcal{B}(0) = (i, 0)$ and $\mathcal{B}(1) = (\mathsf{permu}(i), 0)$

where $\mathsf{permu}(i)$ is the image of an element $i \in N$ through a permutation $\mathsf{permu} : N \to N$ from the set of permutations of N,

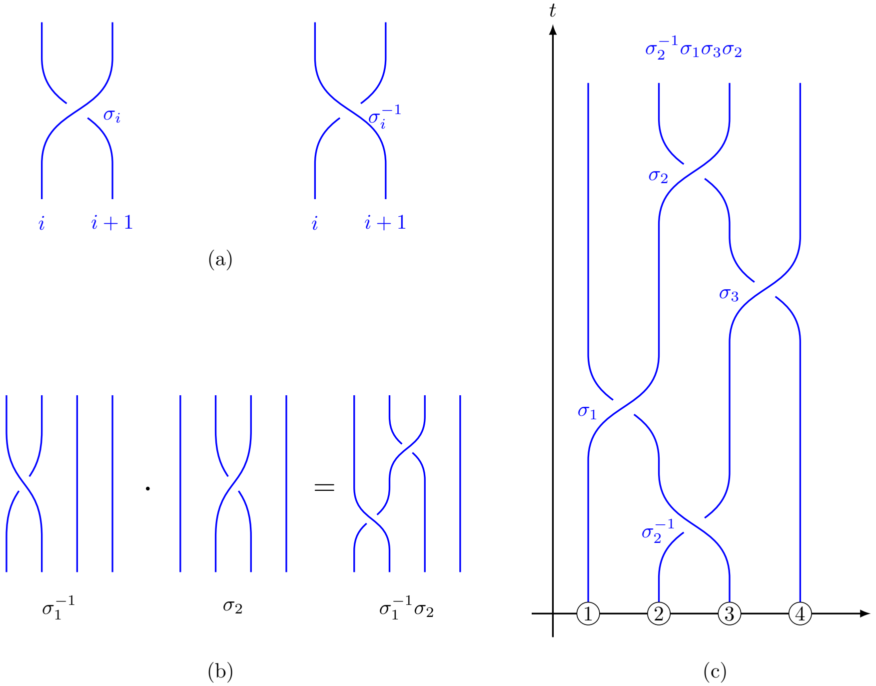


Figure D.1: Braid diagram. (a) Braid generators (or primitives). (b) Algebraical operations. (c) Topological braid diagram: An example of a braid that can be written as a product of generators and generator inverses.

$$\mathsf{permu} = \begin{bmatrix} 1 & 2 & \cdots & N \\ \mathsf{permu}(1) & \mathsf{permu}(2) & \cdots & \mathsf{permu}(N) \end{bmatrix} \tag{D.2}$$

This geometric representation of a braid is commonly treated as a **geometric braid**. In applications, a geometric braid is often represented with a **braid diagram** — a projection of the braid onto the plane $\mathbb{R} \times 0 \times I$.

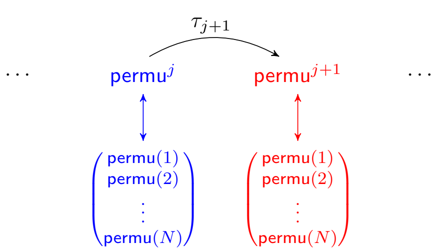
The **set of all braids** on n-strings, along with the composition operation over elementary braids (called braid primitives or generators), form a group B_n generated from a set of $n-1$ elementary braids $\sigma_1, \sigma_2, \ldots, \sigma_{n-1}$. Figure D.1 illustrates the relationship between braid generators, algebraical operations, and braid diagrams.

A **braid generator** σ_i is described as the crossing pattern that emerges upon exchanging the i-th string (counted from left to right) with the $(i+1)$-th string, such that the initially left string passes over the initially right one. The inverse element σ_i^{-1} implements the same string exchange but with the left string passing under the right (see Figure D.1 (a)).

D.2 Joint Strategy

In the multiagent cooperative navigation system, a **joint strategy** refers to a sequence of strategy profiles of all rounds, at each of which each agent i decides an action a_i^k from a set of available actions $\mathcal{A}_i^k$ by maximizing their utilities. Therefore, a joint strategy, τ, of a cooperative game can be represented as

$$\tau = [\tau_1 \tau_2 \dots \tau_K] = [A_1 A_2 \dots A_K] = \begin{bmatrix} a_1^1 & \cdots & a_1^k & \cdots & a_1^K \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ a_i^1 & \cdots & a_i^k & \cdots & a_i^K \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ a_N^1 & \cdots & a_N^k & \cdots & a_N^K \end{bmatrix} \tag{D.3}$$



By treating the whole navigation process as a geometric braid, each agent trajectory profile represents a string of the braid. Thus, each round can be represented by operating on the elementary braid. Specifically, assume N agents generating the whole system path corresponds to a path of permutations. A transition from the j-th permutation permu^j to the $(j+1)$-th permutation permu^{j+1} refers to the occurrence of an

event τ_{j+1}. The event τ_{j+1} may be represented as an elementary braid $\tau_{j+1} \in \{\sigma_{j+1}, \sigma_{j+1}^{-1}\}$.

D.3 Topological Invariance

Consider a closed curve $\rho : [0, T] \to \mathbb{C} \setminus \{0\}$ with $\rho(0) = \rho(T)$ and a well-defined function

$$\lambda(t) = \frac{1}{2\pi i} \oint_{\rho} \frac{dz}{z} \tag{D.4}$$

where $z = \rho(t)$, $t \in [0, T]$. The closed curve $\rho(t)$ can be represented in the polar coordinates as

$$\rho(t) = r(t) e^{i\theta(t)}$$

with $r(t) = \| \rho(t) \|$ and $\theta(t) = \angle \rho(t)$. The Cauchy integral formula makes (D.4) equal to

$$\begin{aligned}
\rho(t) &= \frac{1}{2\pi i} \int_0^t \frac{\dot{r}}{r} d\tau + \frac{1}{2\pi} \int_0^t \dot{\theta} d\tau \\
&= \frac{1}{2\pi i} \log\left(\frac{r(t)}{r(0)}\right) + \underbrace{\frac{1}{2\pi}(\theta(t) - \theta(0))}_{\text{real part}}
\end{aligned} \tag{D.5}$$

What we are interested in is the real part of this integral

$$\mathrm{Re}(\rho(t)) = \frac{1}{2\pi}(\theta(t) - \theta(0)) \tag{D.6}$$

which is a **topological invariant**. Intuitively, Equation (D.6) represents the counting number of times that the curve $\rho(t)$ encircled the origin in the time interval $[0, T]$.

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