A Implementation Details

A.1 Prompting Schema

Slice generation We specifically engineer a prompting schema in a hierarchical fashion. First, we parse the seed idea to identify the specific field and domain:

- `{seed idea} + What fields and domains does the article focus on? Only list the name.`

Then, we use the following prompt to detect evidence:

- `{paper} + Which sentences in the text are about {fields}? List the original sentences.`

Finally, we match the following prompts with the parsed terms to generate an interpretation:

- `{evidence} + What are the motivations in the text for studying {fields}?`
- `What methods and approaches in the text are used to study {fields}?`
- `what theories, models, and methods in the text are proposed to study {fields}?`
- `what results and conclusions in the text related to {fields} are drawn?`
- `what results and conclusions in the text related to {fields} are drawn?`
- `what implications or suggestions in the text for future research of {fields} are advocated?`

Connection generation Our engineered prompt comes in a selective fashion.

- `What are the differences (improve, alternate, compete) between the work {slice_1} and another work {slice_2} on motivations, methods, results, or conclusions to study {fields}?`
- `What are the similarities (inspire, parallel) between the work {slice_1} and another work {slice_2} on motivations, methods, results, or conclusions to study {fields}?`

A.2 Alternate Approach

Slice generation The baseline prompt is simply a direct prompt.

- `{evidence} + What interpretation about {fields} can we get from the text?`

Connection generation The baseline prompt is simply a direct prompt.

- `What are the differences and similarities between the work {slice_1} and another work {slice_2} on studying {fields}?`

B Experimental Details

B.1 Instructions for Participants

Read the abstract, introduction, discussion, and conclusion sections of the following article, and write a short review entitled "Physics-based reasoning" in a txt file using the given process (see the tutorial for instructions; only for the experimental group). The experiments will last for one hour. You can use the Internet to help you write.

1 Holistic 3d Scene Parsing and Reconstruction from a Single RGB Image. ECCV, 2018.

2 Scene Understanding by Reasoning Stability and Safety. IJCV, 2015.

3 Galileo: Perceiving Physical Object Properties by Integrating a Physics Engine with Deep Learning. NeurIPS, 2015.

4 Physics 101: Learning Physical Object Properties from Unlabeled Videos. BMVC, 2016.

5 Understanding Tools: Task-oriented Object Modeling, Learning, and Recognition. CVPR, 2015.

B.2 Interfaces in the Procedures

We show the screenshots of user interactions during the experiments, from entering an input perspective Fig. A1, to selecting papers Fig. A2, generating pieces of evidence Fig. A3, generating slices Fig. A4, generating connections Fig. A5, and browsing the perspective frame Fig. A6. To note, though these steps are demonstrated in a monotonic order here, every step is repeatable and extensible.

B.3 Interview questions

We interview participants on the following two questions.

- How does PersLEARN help you compose reviews?
- How can PersLEARN be improved?

C Extended Results

C.1 Perspective Paragraphs by Subjects

We show anonymized representative examples from both the control group and the experimental group of the human study. All examples are kept original without any revision, including typos. Colored texts are used to **highlight** interpretation and relation respectively facilitated by slices and connections of `PersLEARN` in the experimental group.

The top three paragraphs from the experimental group **with** pertinent interpretations and logical relations:

#1:

> Physics-based reasoning has been used for two aims. The first is to learn the physical properties of an object. For example, Galileo[3] and Physics 101[4] learn physical properties like mass and density from videos. Bo Zheng et al[2] learn stability and safety of objects in a scene. The second is to enrich the object representation by incorporating physical features. The enriched representation is then used to assist other visual tasks. Siyuan Huang et al[1] design a physically enriched HSG representation of 3D scene structure in the single-view 3D reconstruction task. Yixin Zhu et al[5] use a representation consisting four physical-functional components in object recognition task.

#2:

Relatively brief runs of MCMC can drive simultions in physics engine to fit the key features of visual image, which has a simlilarly accurate outcome comparing with human intutions[3]. Further study expand the abilities of learning the basic features of scenes, which makes the 3D parsing and reconstruction real. HSG can establish a joint distribution over the functional and geometric space of scenes, which capatures the latent human context, geometric constraints and physical constraints[1]. By implenting a new framwork, visual system learns the tools properties, the using methods, and the later action to do some related works, which not only recognize the appearance, but also explain the physical mechanisms[5].

#3:

Conventional scene understanding methods mostly neglect the object's physical properties, rendering their weak ability of accurately understanding the scenes. To addess this issue, Zheng et al. [2] proposed a novel 3D scene understanding approach from a new perspective of reasoning object stability and safety using intuitive mechanics. As a step further, Huang et al. [1] proposed a computational framework to jointly parse a single RGB image and reconstruct a holistic 3D configuration, jointly considering latent human context, geometric constraints, and, physical constraints to guarantee the physical plausibility.

The top three paragraphs from the control group which **fail to** interpret and organize from the perspective of physics-based reasoning:

#1:

The five papers all concerns over a main topic, that is how to effectively train artificial intelligence to precieve the outside physical world and afterwards giving different forms of feedback or guidance on new circumstances. The first and second are generally about understanding scenes but have some differences in their domains .The first one using a RGB Image to generate 3D scend applying the Markov chain Monte Carlo (MCMC) method[1], and the second focusing on building novel algorithms which are able to reason object stability and safety using intuitive mechanics with the representation of the disconnecty graphs and disturbance field[2]. They all propose a new perspective for machines to logically and correctly process the human-understood information.

#2:

Machine learning and deep learning are applied to study physical object properties. In 2015, Jiajun Wu proposed a generative model for solving problems of physical scene understanding from real-world videos and imag[3]. As the same time, Yixin Zhu presented a new framework – task-oriented modeling, learning and recognition which aims at understanding the underlying functions, physics and causality in using objects as "tools"[5]. Later in 2016, Jiajun Wu proposed an unsupervised model to learn physical object properties from unlabeled video[4]. Also, physics-based reasoning palys an important role in 3D parse and holistic 3D scene understanding. Bo Zheng presented a new perspective for 3D scene understanding by reasoning object stability and safety using intuitive mechanics[2]. Siyuan Huang proposed a computational framework to jointly parse a single RGB image and reconstruct a holistic 3D configuration composed by a set of CAD models using a stochastic grammar model[1].

#3:

The complexity and richness of human vision are not only reflected by the ability to recognize visible objects, but also to reason about the latent actionable information, including inferring physical object properties[4] or latent human context as the functionality of a scene[1]. But how does human vision achieve such complexity and richness ? Some studies propose a model based on physics principle for understanding these mechanisms[2,3,4]. Even other sudies consider more complex situations, where humans have tasks[5] and other hidden human context[1].

C.2 Slices Generated by Machines

We present several examples of the generated slices with their BLEURT scores from the pipeline with and without prompt engineering.

#1: w/o: -1.132

> The article suggests that deep learning, adversarial attacks, and countermeasures are independent of the data miner's activities.

#1: w/: 0.326

> The article focuses on the motivations for studying deep learning, adversarial attacks, and countermeasures in order to better understand and defend against data manipulation by adversaries. The paper uses deep learning, adversarial attacks, and countermeasures to study the problem. The paper proposes a formal framework and algorithms for studying deep learning, adversarial attacks, and countermeasures. It also discusses theories, models, and methods related to these fields and domains. The article suggests that future research should focus on developing deep learning systems that are more robust to adversarial attacks and require less human intervention to keep up with them.

#2: w/o: -1.090

> The article suggests that understanding the cognitive development, infant development, and developmental psychology of others is essential for successful social interactions.

#2: w/: 0.616

> The article uses a variety of methods and approaches to study the fields of cognitive development, infant development, and developmental psychology. These include observational studies, experiments, and surveys. The article also uses a variety of theoretical frameworks, such as Piaget's theory of cognitive development, to analyze the data. The strengths of the text are that it provides evidence of infants' anticipatory responses to others' actions from an early age, and it also provides evidence that infants attend prospectively to others' actions. The limitations of the text are that it does not clarify whether infants anticipated the goal per se because the goal and pattern of movement were confounded.

#3: w/o: -0.735

> Sentiment analysis, news categorization, question answering, and natural language inference are all techniques used to analyze text and extract meaning from it.

#3: w/: 0.422

> The methods and approaches used to study sentiment analysis, news categorization, question answering, and natural language inference in the text include supervised learning, unsupervised learning, deep learning, natural language processing, and machine learning. The theories, models, and methods proposed to study sentiment analysis, news categorization, question answering, and natural language inference in the text are Convolutional Neural Networks (CNNs) and SVMs with well-engineered features.

C.3 Connections Generated by Machines

Our pipeline can discover the similarities and differences between slices. Below are some representative connections the model generatesgenerated by the model with and without prompt engineering.

#1: w/o

The two works have similar motivations for studying Knowledge Graph Representation Learning, Knowledge Acquisition and Completion, Temporal Knowledge Graph, and Knowledge-Aware Applications. The methods used in the two works are also similar, with Knowledge Graph Representation Learning typically involving graph embedding, graph convolutional networks, and graph neural networks, Knowledge Acquisition and Completion typically involving rule-based approaches, ontology-based approaches, and machine learning-based approaches, Temporal Knowledge Graphs typically involving temporal graph embedding, temporal graph convolutional networks, and temporal graph neural networks, and Knowledge-Aware Applications typically involving knowledge-aware recommendation systems, knowledge-aware question answering systems, and knowledge-aware search systems. The results and conclusions of the two works are also similar, with Knowledge Graph Representation Learning theories, models, and methods including graph embedding, graph convolutional networks, graph attention networks, and graph generative models, Knowledge Acquisition and Completion methods including rule-based methods, ontology-based methods, and machine learning-based methods, Temporal Knowledge Graph methods including temporal graph embedding, temporal graph convolutional networks, and temporal graph attention networks, and Knowledge-Aware Applications including question answering, recommendation systems, and natural language processing.

#1: w/

The two works have similar motivations, methods, results, and conclusions when it comes to studying Knowledge Graph Representation Learning, Knowledge Acquisition and Completion, Temporal Knowledge Graph, and Knowledge-Aware Applications. The main difference between the two works is that the first work focuses on how knowledge graphs can be used to extract relations from text and can be used for knowledge acquisition and completion, while the second work provides an overview of the topics and suggests that they are related and can be used to develop applications that are aware of knowledge.

#2: w/o

The motivations for studying Artificial Intelligence, Cognitive Science, Pattern Recognition, Physics, and Psychology in the text are to gain a better understanding of how humans learn and process information, and to develop algorithms that can learn from fewer examples than traditional machine learning algorithms. The methods used in the text are theories, models, and methods from Artificial Intelligence, Cognitive Science, Pattern Recognition, Physics, and Psychology to study simple visual concepts. The results of the text suggest that future research should focus on understanding how people learn new concepts from just one or a few examples, and how people learn such abstract, rich, and flexible representations. The conclusion of the text is that any theory of concept learning should address these questions and provide implications or suggestions for future research in Artificial Intelligence, Cognitive Science, Pattern Recognition, Physics, and Psychology.

#2: w/

The two works have similar motivations in studying Artificial Intelligence, Cognitive Science, Pattern Recognition, Physics, and Psychology. The methods used in both works are similar, as they both suggest combining multiple levels of representation with the flexible use of long range context. The results of the first work suggest that deep Long Short-term Memory RNNs are a powerful model for sequential data and can be used for tasks such as cursive handwriting recognition and phoneme recognition. The results of the second work suggest that Artificial Intelligence, Cognitive Science, Pattern Recognition, Physics, and Psychology have not been able to replicate two aspects of human conceptual knowledge. The conclusions of both works are that combining multiple levels of representation with the flexible use of long range context can lead to improved results.

C.4 Slices for Different Perspectives

We show some interpreted slices of two cited papers (indexed by #) from different perspectives (*italicized*). These two papers are:

1 Heuristic judgment of mass ratio in two-body collisions. Perception & Psychophysics 56 (1994): 708-720.

2 Learning a theory of causality. Psychological Rreview 118.1 (2011): 110.

#1: *Intuitive Physics: Current Research and Controversies*

Intuitive Physics, Perception, Reasoning, and Artificial Intelligence are all studied in order to gain a better understanding of how the world works and how to create more efficient and effective systems. These fields are also studied in order to develop new technologies and applications that can be used to improve the lives of people. Methods and approaches used to study Intuitive Physics, Perception, Reasoning, and Artificial Intelligence include computational modeling, cognitive psychology, neuroscience, and machine learning.Theories, models, and methods proposed to study Intuitive Physics, Perception, Reasoning, and Artificial Intelligence include Bayesian inference, probabilistic graphical models, deep learning, reinforcement learning, and evolutionary algorithms. The results and conclusions drawn from the text related to Intuitive Physics, Perception, Reasoning, and Artificial Intelligence are that humans have an innate ability to understand physical concepts and use them to make decisions and solve problems. This suggests that humans have an intuitive understanding of physics that can be used to inform Artificial Intelligence algorithms. Additionally, the text suggests that humans are capable of making decisions and solving problems based on their perception of the physical world, and that this ability can be used to inform Artificial Intelligence algorithms.

#1: *Mind Games: Game Engines as an Architecture for Intuitive Physics*

The motivations for studying Artificial Intelligence, game development, and physics simulation are to gain a better understanding of how these technologies work, to develop new applications and technologies, and to explore the potential of these technologies for solving real-world problems. Artificial intelligence, game development, and physics simulation can be studied using a variety of methods and approaches, including machine learning, deep learning, reinforcement learning, evolutionary algorithms, and probabilistic methods. Artificial intelligence, game development, and physics simulation can be studied using a variety of theories, models, and methods. These include machine learning, deep learning, reinforcement learning, evolutionary algorithms, game theory, and physics-based simulations. Strengths of the text for studying Artificial Intelligence, game development, and physics simulation include its comprehensive coverage of the topics, its use of examples to illustrate key concepts, and its clear explanations of complex topics. Limitations of the text include its lack of in-depth coverage of certain topics and its lack of discussion of the latest developments in the field.

#2: *Bayesian Models of Conceptual Development: Learning as Building Models of the World*

The motivations in the text for studying Cognitive Development, Core Knowledge, Child as Scientist, Bayesian Program Induction, Computational Advances, Scientific Theories, Intuitive Theories, Biological Evolution, and Cultural Evolution are to gain a better understanding of the principles of causal reasoning and to develop a more comprehensive account of causality. Cognitive Development, Core Knowledge, Child as Scientist, Bayesian Program Induction, Computational Advances, Scientific Theories, Intuitive Theories, Biological Evolution, and Cultural Evolution are all methods and approaches used to study the blessing of abstraction. Cognitive Development, Core Knowledge, Child as Scientist, Bayesian Program Induction, Computational Advances, Scientific Theories, Intuitive Theories, Biological Evolution, and Cultural Evolution are all theories, models, and methods proposed to study Cognitive Development, Core Knowledge, Child as Scientist, Bayesian Program Induction, Computational Advances, Scientific Theories, Intuitive Theories, Biological Evolution, and Cultural Evolution.

#2: *Intuitive Theories*

The motivations in the text for studying Cognitive science, psychology, and philosophy are to gain a better understanding of the principles of causal reasoning and to develop a description of the principles by which causal reasoning proceeds. Cognitive science, psychology, and philosophy are studied using methods and approaches such as logical reasoning, empirical observation, and experimentation. Cognitive science, psychology, and philosophy are studied using theories, models, and methods such as Bayesian networks, causal inference, and counterfactual reasoning. The results and conclusions drawn from the text related to Cognitive science, psychology, and philosophy are that abstract reasoning can be used to quickly learn causal theories, and that this can be beneficial in certain situations.

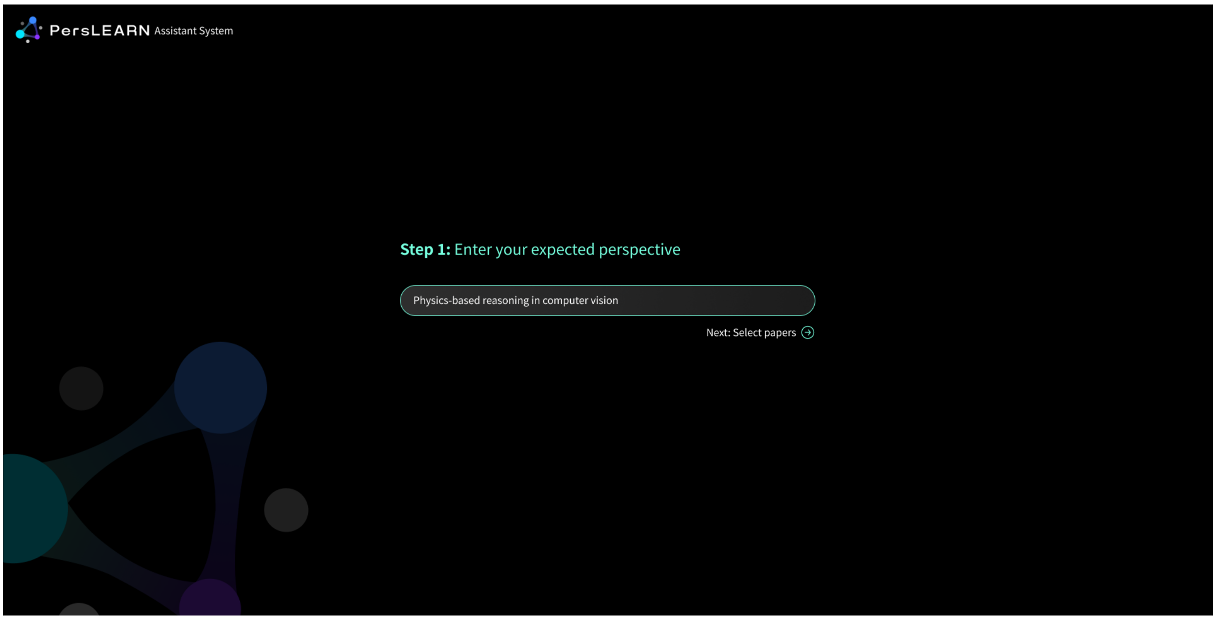

Figure A1: **Input seed idea**

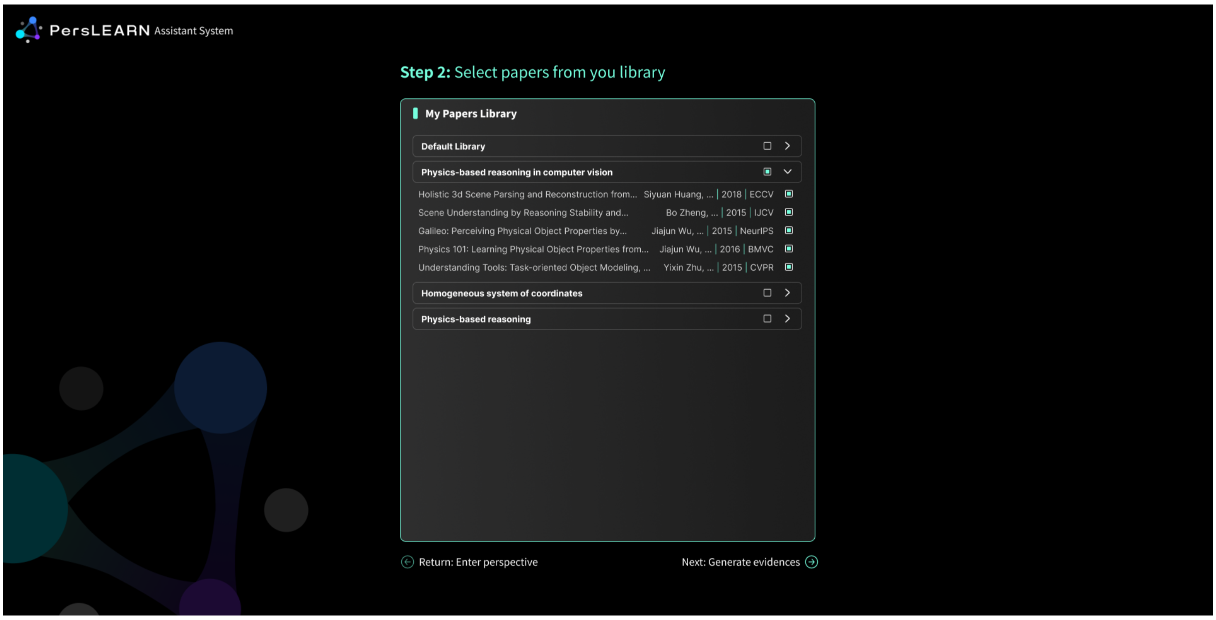

Figure A2: **Select papers**

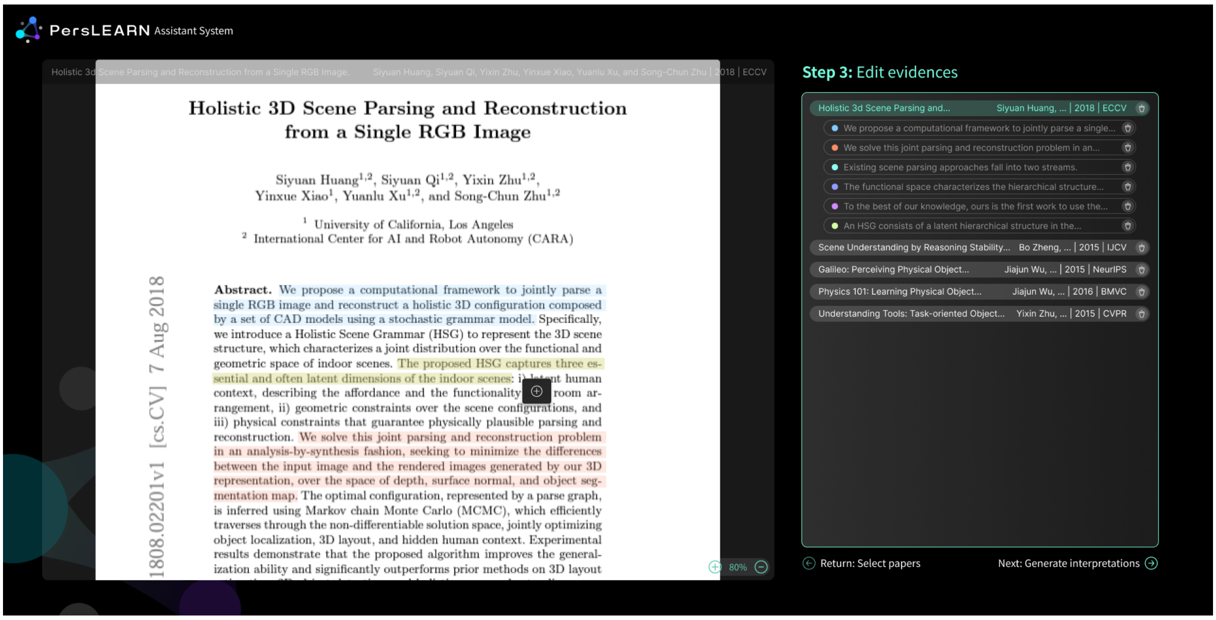

Figure A3: **Append and edit evidences**

Figure A4: **Append and edit slices**

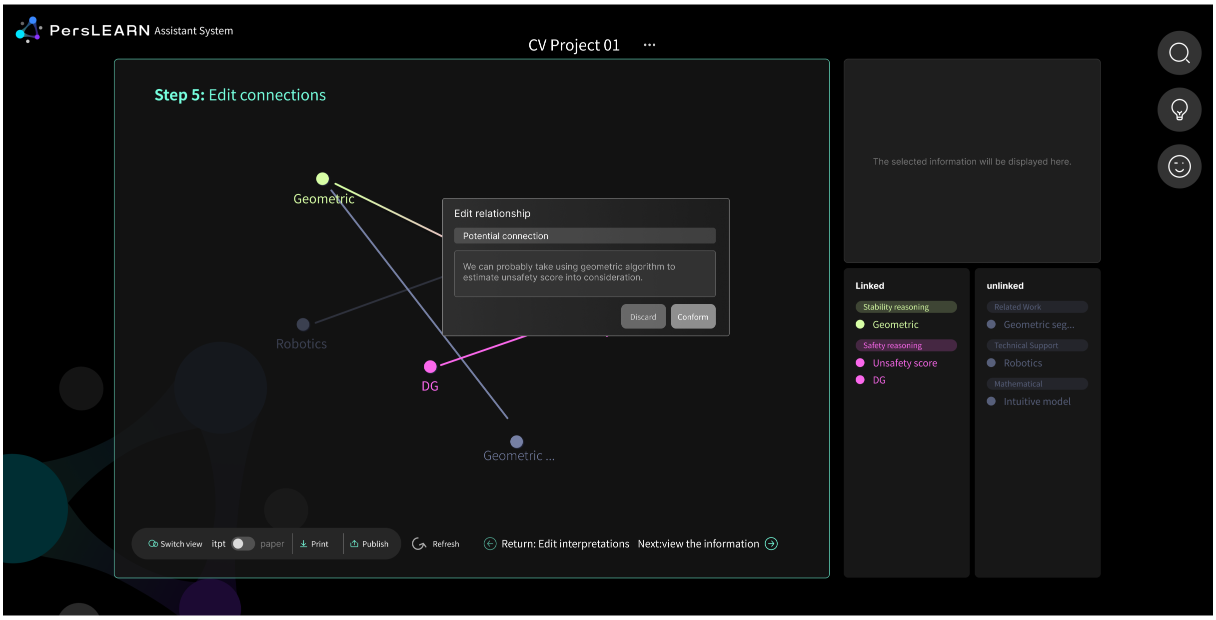

Figure A5: **Append and edit connections**

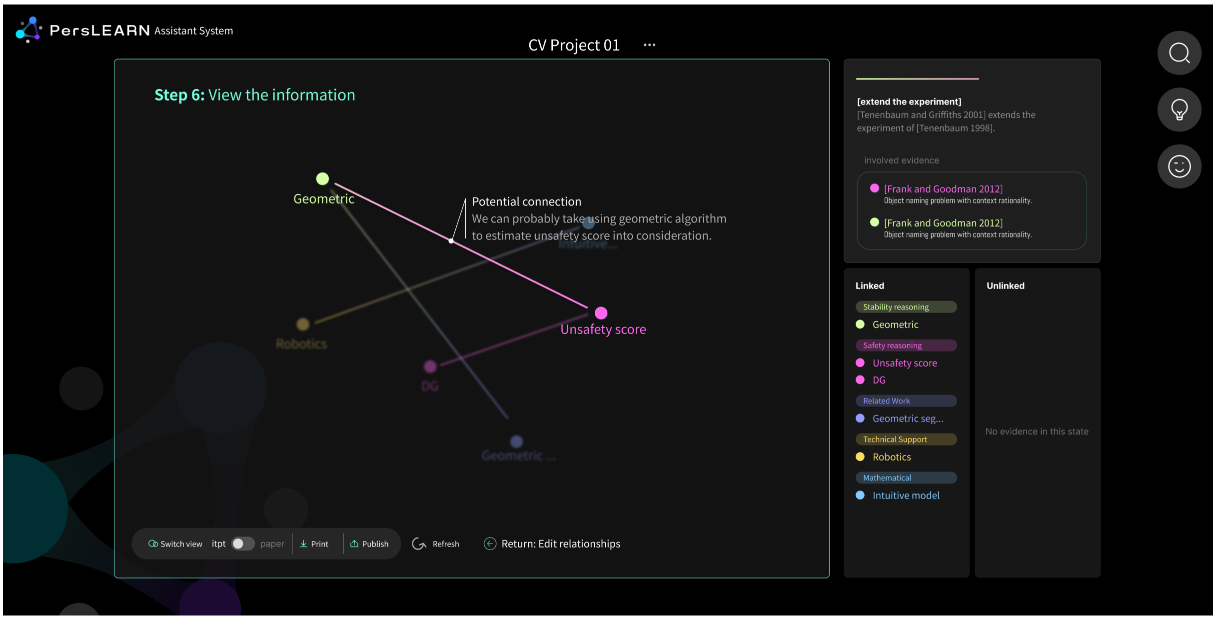

Figure A6: **Browse information of the perspective frame**