

Abstract

AI-powered mobile apps often fail to provide clear explanations for their decisions. MIT App Inventor Punya is an Android app development software that includes a rule-based reasoner, but it offers limited insight into its reasoning process. To foster user trust, interpretable explanations are essential for making complex AI/ML decision-making processes more transparent.

Introduction

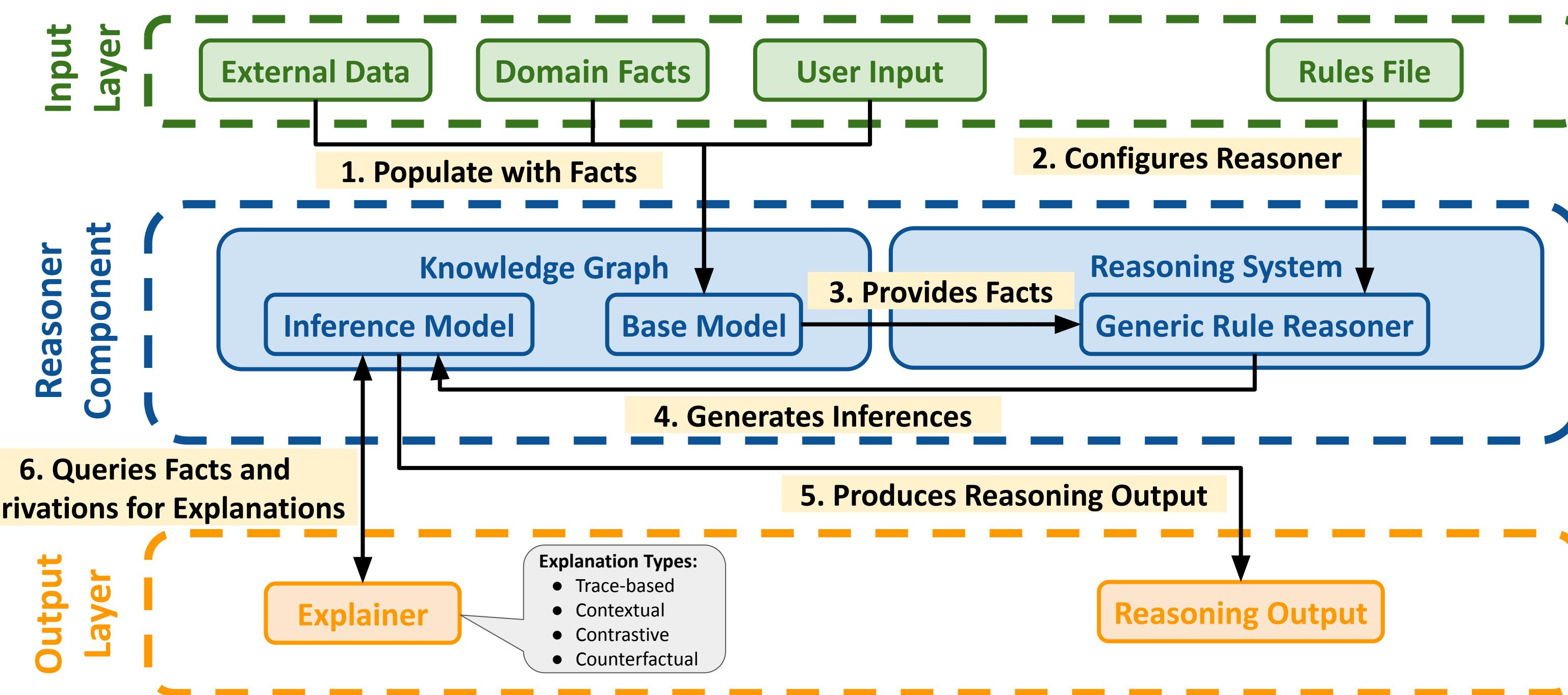
- AI systems often make decisions without revealing their reasoning, posing challenges in critical fields like healthcare, finance, and law
- Transparency is essential for users to trust and verify decisions that impact lives
- Decisions are represented using RDF (Resource Description Framework) triples:
 - Subject: The entity (e.g., loan applicant)
 - Predicate: The relationship/attribute (e.g., credit score)
 - Object: The value/outcome (e.g., "Eligible")

Explanation Types

Explanation	Definition
Trace-based	<ul style="list-style-type: none"> Shows step-by-step reasoning chain Explains "how" the system reached its conclusion Maps reasoning rules to input facts
Contextual	<ul style="list-style-type: none"> Considers surrounding circumstances Includes user situation and environment Explains relevance of external factors
Contrastive	<ul style="list-style-type: none"> Compares different outcomes Highlights key differences between scenarios Explains why a result occurred instead of another
Counterfactual	<ul style="list-style-type: none"> Explores "what-if" scenarios Shows how changing inputs affects outcomes Identifies minimal changes needed for different results

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Reasoning Architecture



Example Explanations

Base Knowledge

Model evaluates loan applications using RDF triples that represent:

- Applicant attributes (credit score, monthly income, monthly debt)
- Calculated metrics (DTI ratio = monthly debt/monthly income)
- Decision outcomes (Eligible or Not Eligible)

Input Triple: (applicant1, loanEligibility, Not Eligible)

Trace-Based

Conclusion: applicant1 has Loan Eligibility: Not Eligible used the following matches:

Match: applicant1 has Type: Person
 Match: applicant1 has DTI Ratio: 0.4
 Conclusion: applicant1 has DTI Ratio: 0.4 used the following matches:
 Match: applicant1 has Type: Person
 Match: applicant1 has Monthly Debt: 2000.0
 Match: applicant1 has Monthly Income: 5000.0
 And paired them with the following rule:
 [[DTIRule: (?applicant type Person) (?applicant monthlyDebt ?debt) (?applicant monthlyIncome ?income) quotient(?debt ?income ?dti) -> (?applicant dtiRatio ?dti)]]
 to reach this conclusion.

And paired them with the following rule:
 [[NotEligibleDTIRule: (?applicant type Person) (?applicant dtiRatio ?dti) greaterThan(?dti '0.349999') -> (?applicant loanEligibility 'Not Eligible')]]
 to reach this conclusion.

Contrastive

Similarities:

- applicant1 has Monthly Income: 5000.0

Differences:

- For Monthly Debt: this model has 2000.00 while alternate model has 1000.00
- For Loan Eligibility: this model has Not Eligible while alternate model has Eligible
- For Credit Score: this model has 680 while alternate model has 700
- For DTI Ratio: this model has 0.40 while alternate model has 0.20

Contextual

Shallow Explanation:

Conclusion: applicant1 has Loan Eligibility: Not Eligible
 Based on rule: [NotEligibleDTIRule: (?applicant type Person) (?applicant dtiRatio ?dti) greaterThan(?dti '0.349999') -> (?applicant loanEligibility 'Not Eligible')]

Using the following facts:

- applicant1 has Type: Person
- applicant1 has DTI Ratio: 0.4

Simple Explanation:

applicant1 has Loan Eligibility: Not Eligible because applicant1 has Type: Person and applicant1 has DTI Ratio: 0.4.

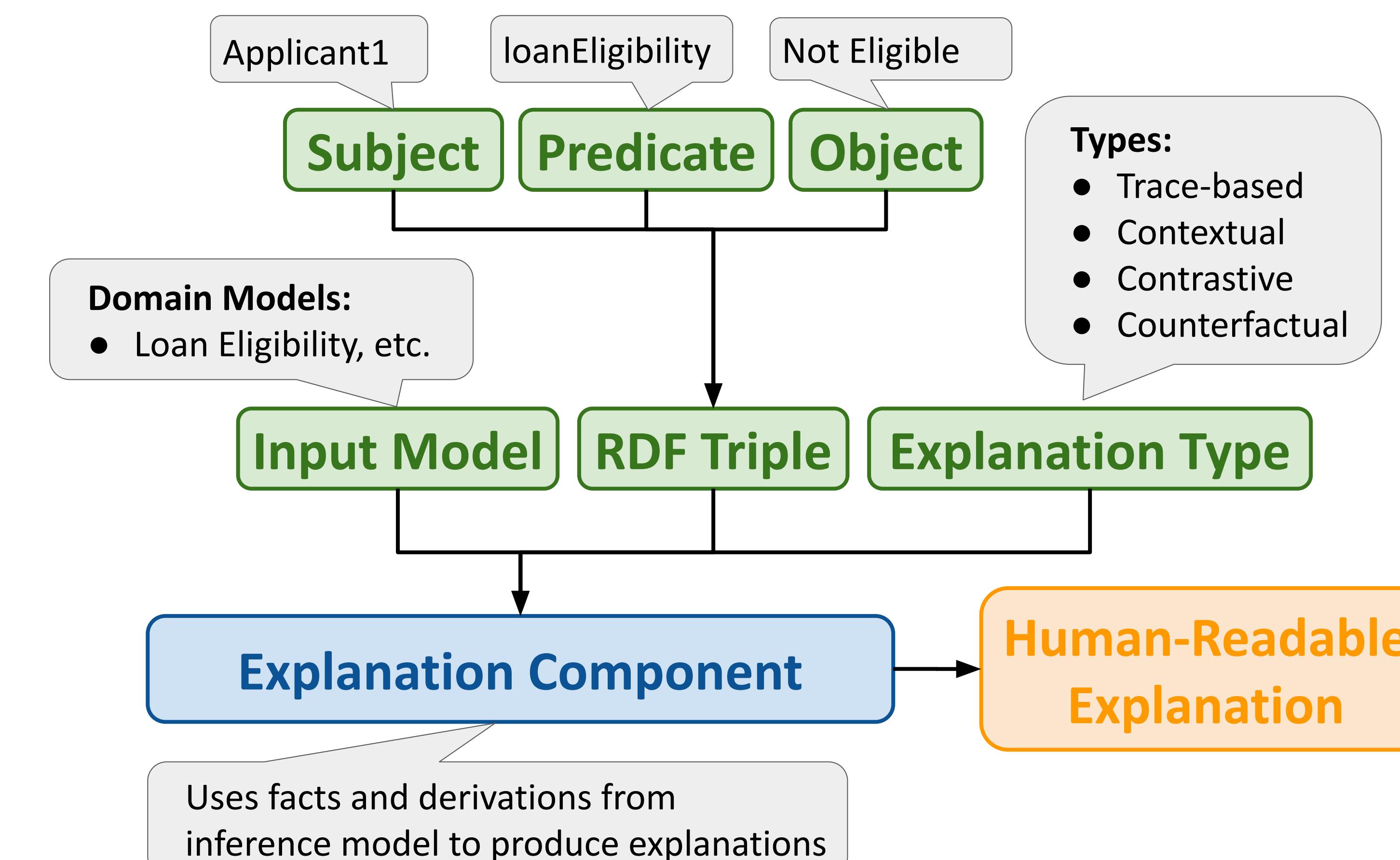
Counterfactual

To change the outcome for applicant1 has Loan Eligibility: Not Eligible, you could look at these examples:

applicant3 has Loan Eligibility: Eligible because:

- Their applicant3 has DTI Ratio: 0.2 while yours is applicant1 has DTI Ratio: 0.4
- Their applicant3 has Monthly Debt: 1000.0 while yours is applicant1 has Monthly Debt: 2000.0
- Their applicant3 has Credit Score: 700 while yours is applicant1 has Credit Score: 680

Explanation Component



Conclusion

- Successfully implemented multiple explanation types for MIT App Inventor Punya reasoning component
- Created a framework for future expansion to more explanation types
- Demonstrated feasibility for explainer component on mobile devices

Future Work

- Integration with more complex AI models (Neural networks)
- Expand offerings for explanation types
- Optimize explanation outputs with NLP and accuracy scores
- Perform user studies on explanation effectiveness
- Deploy explanation component into MIT App Inventor Punya subproject

References

[1] S. Chari et al., "Explanation Ontology: A general-purpose, semantic representation for supporting user-centered explanations," Semantic web, pp. 1–31, May 2023, doi: <https://doi.org/10.3233/sw-233282>.