Towards a Holistic Integration of Energy Justice and Energy System Engineering

Preliminary Exam

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4. Theory of Model Development
   - Pre-Descriptive: Normative-Parametric
   - Descriptive: Parametric-Structural
   - Prescriptive: Structural-Normative

Presentation Goals

I have the following goals for this presentation:

1. **Motivate** why social science and quantitative modeling *must* be more strongly integrated (based on the relations among three types of uncertainty).
2. **Demonstrate** how `Osier` currently accomplishes this goal.
3. **Propose** future work to enhance `Osier`'s capabilities and validate its usage.

and I hope to show the **layered novelty** of this work as a corrolary of the above.

Proposal Overview

I propose to:

1. **Deepen** the theoretical foundations of this work.
2. **Develop** an optimization tool (`Osier`) that
   - addresses three related uncertainties,
   - closes the gap between technical expertise and public preferences,
   - enhances justice outcomes related to energy planning.
3. **Validate** this tool by conducting a case study of energy planning processes in the Champaign-Urbana region.

Outline I

Climate change exists and *we're causing it*!

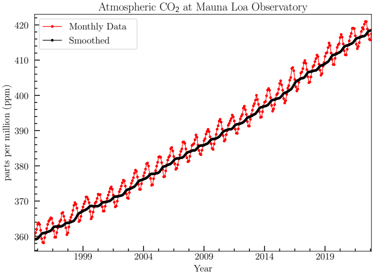


Figure 1: Observed increase in CO_2 levels at Mauna Loa Observatory [16].

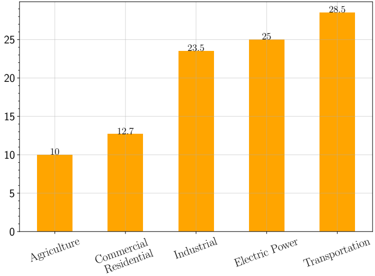


Figure 2: Carbon emissions by economic sector [8]

We have the technology to stop using fossil fuels

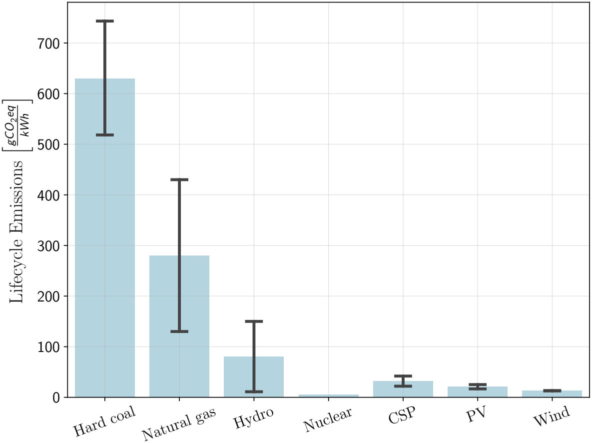


Figure 3: Lifecycle carbon emissions by energy source [30].

… and yet

1. Most climate change mitigation policies will overshoot U.N. emissions targets [26]
2. and there is still local public opposition to clean energy projects [1, 10, 28]

Motivating Questions

Question #1

What drives public opposition to clean energy projects?

Question #2

How does energy modeling contribute to this problem?

What drives opposition? It's not NIMBY

1. NIMBY is popularly understood to drive opposition.
2. However, several case studies and larger surveys have demonstrated that this is not the case [21, 1].
3. Instead, perceptions of legitimacy in decision-making processes motivates this opposition [11, 28, 1, 32, 22].
4. Public testimony may be dismissed for being nontechnical casting doubt on legitimacy [15].

Final Motivating Question

Question 3

How can members of the lay public adequately deliberate on issues perceived by experts as highly technical?

Gap #1: Incomplete understanding of uncertainty

Climate change is a “wicked problem” with many uncertainties [13].
Policies derived from theory or modeling practices ignorant of these uncertainties is partially responsible for the paradox identified previously.
A more comprehensive understanding of these uncertainties will inform better modeling practices and more just solutions.

Proposal #1: Understanding Uncertainty

1. Develop a theoretical framework to conceptualize different uncertainties and their interrelationships.
2. Connect this framework to *justice*, specifically Schlosberg's three-tenet paradigm [27].

Outline I

Triarchic Theory of Model Development

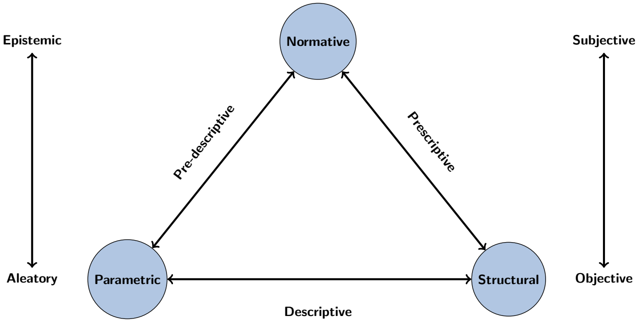
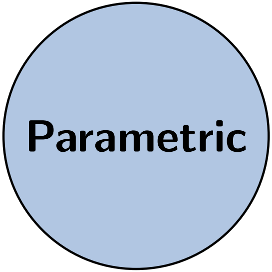


Figure 4: A summary of three uncertainties and their interactions.

Parametric Uncertainty



Parametric Uncertainty

Related to uncertainty in model inputs (empirical values). The most commonly addressed type of uncertainty in science and engineering [37, 4, 23].

May be classified as either **aleatory** or **epistemic** [24, 19].

Examples of Parametric Uncertainty

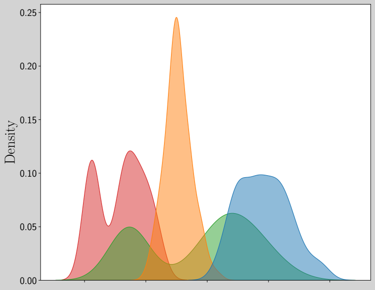


Figure 5: Possible distributions of several parameters.

- Rates (e.g., interest, learning, growth),
- costs (e.g., fuel, capital, O&M),
- aggregated energy demand,
- spent fuel burnup [9],
- nuclear cross-section data [6, 25],
- likelihood and magnitude of consequences (i.e., probabilistic risk assessment).

Consequences of not addressing parametric uncertainty

A majority of ESOM articles use *scenario analysis* to weakly ddress parametric uncertainty [37].

Leading to:

1. Overconfidence in results
2. Cognitive myopia
3. Implicit normative biases

Addressing parametric uncertainty

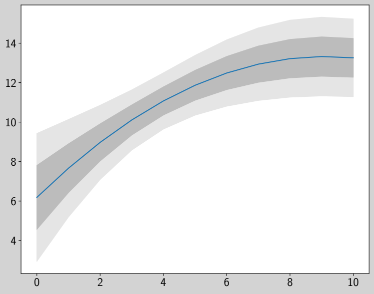


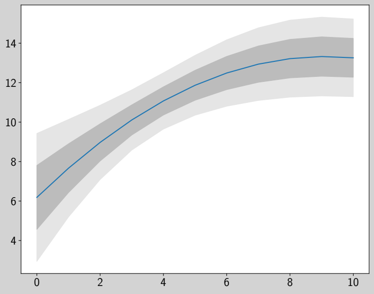
Figure 6: Systematically addressing parametric uncertainty produces confidence intervals.

Idea: Rerun a simulation until you reach a large enough sample size to do statistics.

Formal methods to address parametric uncertainty*:

- "Monte Carlo" (i.e., statistical sampling)

Addressing parametric uncertainty



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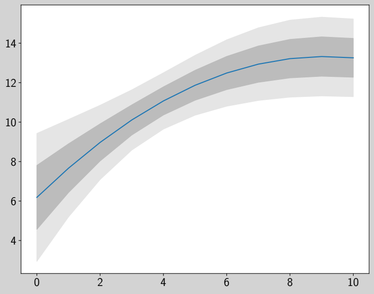

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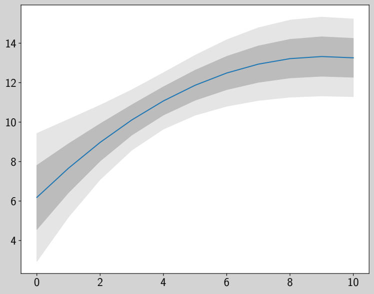

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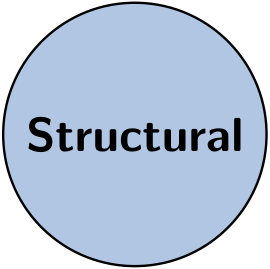
- “Monte Carlo” (i.e., statistical sampling)
- Sensitivity analysis (specific or global)
- Stochastic optimization

*These methods are appropriate for **aleatory** uncertainties.

Structural Uncertainty



Structural Uncertainty

[R]efers to the imperfect and incomplete nature of the equations describing the system [4].

This type of uncertainty will *always* persist.

Examples Sources of Structural Uncertainty

Unmodeled or unmodelable aspects of the model related to:

1. Objective functions
2. Physics fidelity, for example
   - optimal power flow,
   - turbulence (air flow, water flow, etc.),
   - thermodynamics (e.g., weather impacting a power plant's ultimate heat sink)

Consequences of unhandled structural uncertainty

1. Overconfidence in results
2. Cognitive myopia
3. Missed acceptable alternatives

Addressing Structural Uncertainty

Idea: Look for alternatives in the "near-optimal" space.

How? Modeling-to-generate-alternatives (MGA)

1. **Relax** the objective function.
2. **Search** for maximally different solutions in the design space.
3. **Iterate** until enough solutions have been generated.

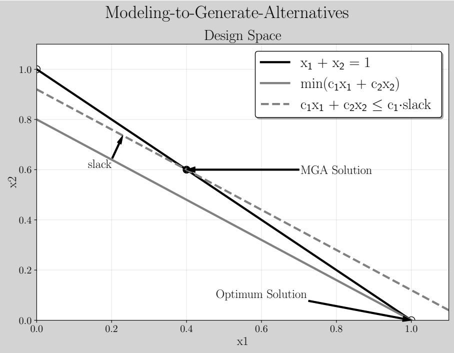
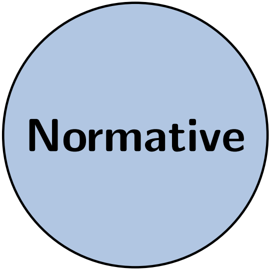


Figure 7: Illustration of the MGA algorithm.

Normative Uncertainty



Normative Uncertainty

Arises from the plurality of morally defensible, but incompatible, choices; and a plurality of moral theories justifying those choices [29, 31].

Consequences of unacknowledged normative uncertainties

1. Implicit normative premises cannot be debated,
2. Precludes alternative formulations of *justice*,
3. Raises doubts about legitimacy of conclusions.

Addressing Normative Uncertainty

There are no formal methods to address normative uncertainty...

Addressing Normative Uncertainty

There are no formal methods to address normative uncertainty...*in engineering.*

Gap #2: Challenges with current ESOM practices

1. Structural Uncertainty
   - $\sim$100% of ESOM frameworks optimize cost.
   - Stanard MGA procedures anchor alternatives to cost — no true tradeoff analysis.
2. Normative Uncertainty: Most ESOM analyses are prescriptive, few if any articulate a normative premise to justify their conclusions.
   - "Pathway to 100% Renewable Energy..." — a commonly unjustified normative conclusion, right in the title!
   - Why should non-renewable sources be excluded? Renewable energy is not guaranteed to be democratic [34], nor sustainable [3].

Proposal #2: Building a flexible ESOM

1. Create an open-source multi-objective energy system model (`osier`) that can allow modelers to address
   - parametric,
   - structural,
   - and normative uncertainties.
2. Develop an MGA algorithm for use with genetic algorithms in higher dimensional spaces.

How Osier handles structural uncertainty

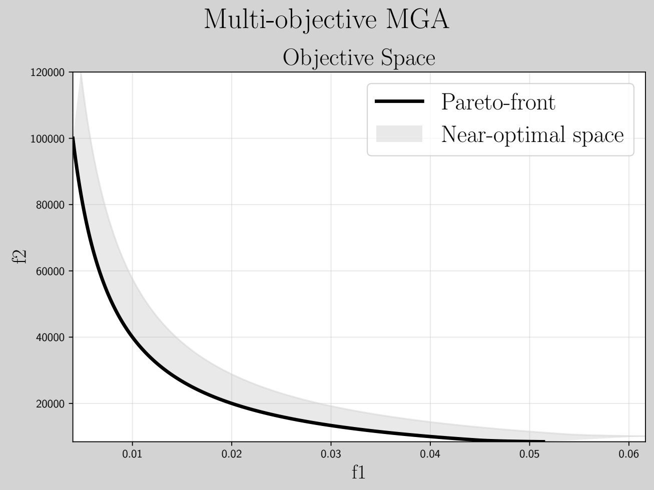


Figure 8: Near optimal space for a multi-objective problem.

How Osier handles structural uncertainty

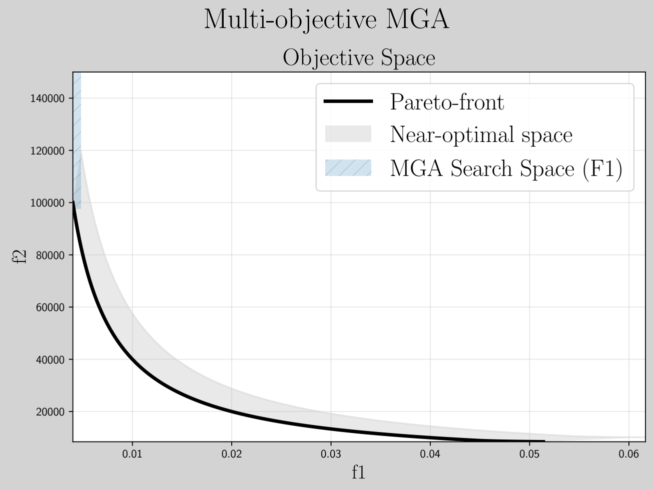
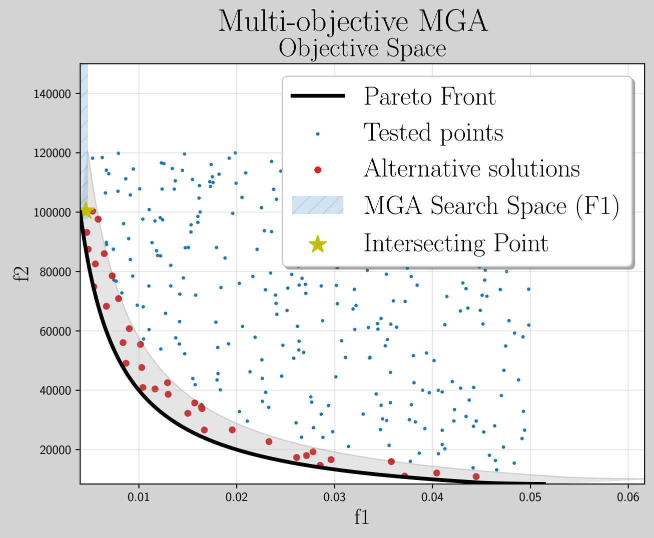


Figure 9: Near optimal space for mono- and multi-objective problems. The light blue area shows a vertically truncated near-optimal space around the f1 objective.

How Osier handles structural uncertainty



Demonstration on a real problem

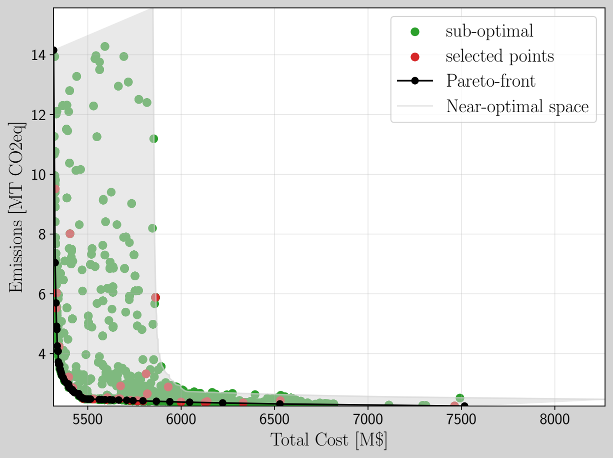


Figure 11: Comparing the results from `Osier` with another ESOM, `Temoa`.

Demonstration on a real problem

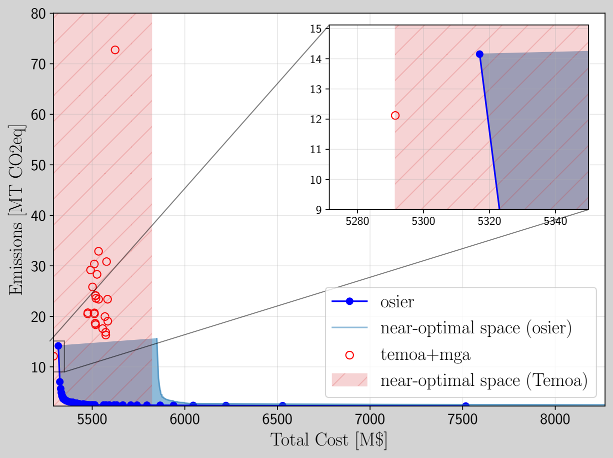


Figure 12: Comparing the results from `Osier` with another ESOM, `Temoa`.

Demonstration on a real problem

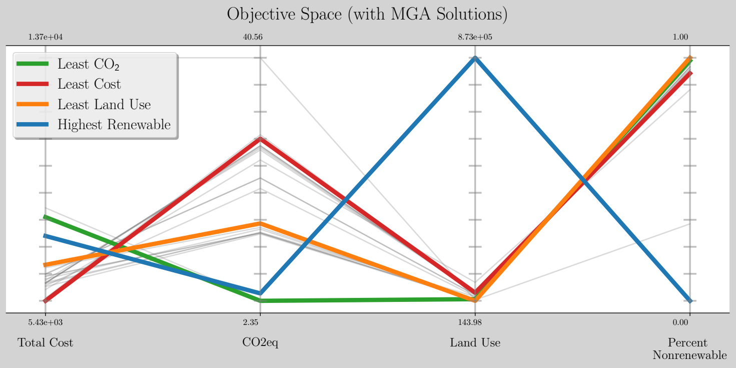


Figure 13: Pareto front and near-optimal solutions for the same problem with 4 objectives.

Demonstration on a real problem

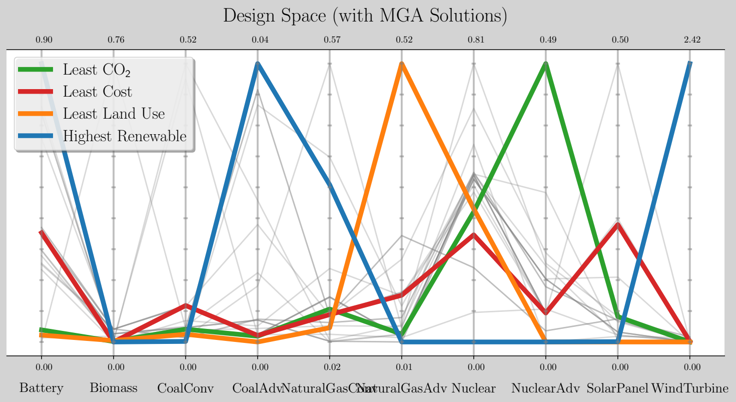


Figure 14: Design space for the 4-objective problem with near-optimal solutions.

Demonstration on a real problem

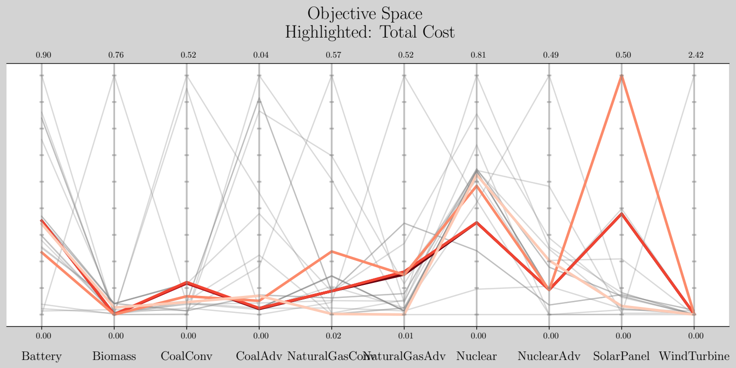
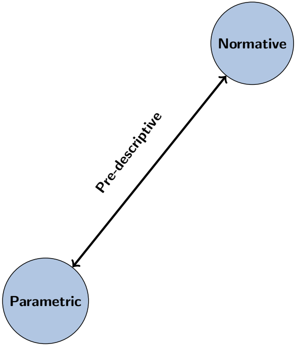


Figure 15: The five lowest cost solutions. Darker shade corresponds to lower cost.

Outline I

How normativity influences parametric uncertainty



Related to model inputs, modelers may:

- **Curate** input data from other sources,
- **Generate** data from prior model runs,
- **Produce** an input distribution from experience.

How are representative probability distributions chosen?

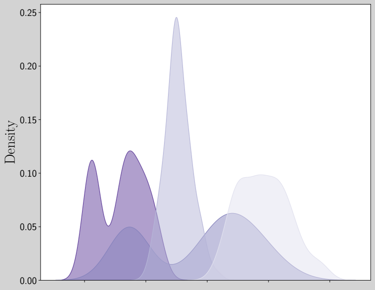


Figure 16: Possible distributions for a single parameter. Which is best?

The probability distributions are usually obtained through modelers' judgement or expert elicitations [37].

Problem: Without understanding how or why a modeler created or chose a distribution, the twin goals of reproducibility and transparency are challenged.

What influences the choice of probability distribution?

Knightian/Deep/Epistemic Uncertainty

Unknowable unknowns — uncertainties that cannot be quantified or measured due to a lack of knowledge or understanding [20].

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Ambiguity Aversion / Ellsberg Paradox

A decision maker will choose a highly risky option with quantifiable uncertainties over an option with deep uncertainties [7].

Considerations with Ambiguity Aversion

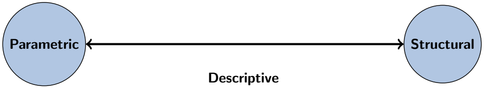
For those highly **epistemic** uncertainties...

1. Awareness of the Ellsberg Paradox does not alleviate ambiguity aversion [14].
2. Ambiguity aversion produces a cautionary shift (i.e. more conservative estimation) [18].

Descriptive: Parametric-Structural

This is where the "research question" lives.

- What is being modeled (i.e. what are the in/dependent variables)?
- How are time series represented? (e.g., weather / demand data)?
- Which technologies are included in the simulation?
- What is the spatiotemporal scale/resolution of the model?

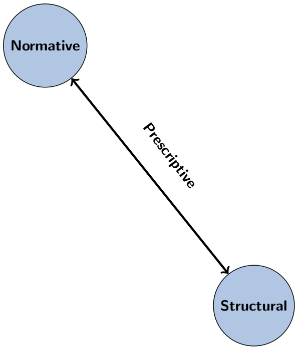


Choosing among alternatives

Generating prescriptive conclusions is the primary reason to model energy systems [4].

Arrow's Impossibility Theorem

It is impossible to construct a utility function that maps individual preferences onto a global preference order without imposition or dictating [17, 12, 2].



Consequences of Arrow's Theorem

1. There is no one-size-fits-all method for public engagement or decision-making.
2. The methods of engagement must "open up" debate rather than "close it down" [33, 5].
3. Ideals of justice and "just outcomes" can never be adequately captured by an aggregated "metric" — this would imply a utility function that could map individual preferences to a collective preference.

Potential Pitfalls

1. Reproducing errors of "public understanding of science" and the "deficit model" [35, 36].

Gap #3: Overcoming Arrow's Theorem

1. Deciding among alternative solutions is challenging without a normative premise.
2. Without direct consultation of stakeholders, it's impossible know how they would understand tradeoffs.
3. Capturing the "human dimension" requires incorporating formal methods from social science: case studies, interviews, focus groups, surveys, etc. The ESOM literature struggles to do this.

Proposal #3: Finding a vision through interlocution

Overcoming Arrow's theorem through an iterative articulation of values and priorities involving the public as key deliberators.

1. Expand Osier to allow modelers to address normative uncertainty.
2. Develop a deliberation procedure that incorporates osier.
3. Case study in the Champaign-Urbana region to consider the normative uncertainties produced by having an unranked set of options.

Acknowledgement

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