All comments will be made public as-is, with no edits or redactions. Please be careful to not include co personal information, otherwise sensitive or protected information, or any information you do not

Comment Template for Responses to NIST Artifical Intelligence Risk Management Framework Request for Infromation (RFI)

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General RFI Topics (Use as many lines as you like)	**Response #**	**Responding organization**	**Responder's name**	**Paper Section (if applicable)**	**Response/Com (Include ration**
Responses to Specific Request for information (pages 11,12, 13 and 14 of the RFI)					
1. The greatest challenges in improving how AI actors manage AI-related risks – where “manage” means identify, assess, prioritize, respond to, or communicate those risks;		Corner Alliance, Inc.		CVPR 2021 Workshop on Autonomous Vehicles (https://www.youtube.com/watch?v=YZTlaiu_vWE)	In the rapidly ch of AI, there are challenges in im AI actors manag risks. As with ot changing fields, known knowns; unknowns; and unknowns of AI modes. Current greatest challen management po inability to antic failure. Until the defines a comp of model suscep gender and raci adversarial exa manipulation to this weakness i to measure and upon. Therefore imperative to id comprehensive schema of what wrong in a mod performance, a rigorously agair factors. This need to cle categories and failure modes a weaknesses is

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					industry to impl guidance becau were to take thi own, the undert be insufficient a without referen document. Addi might include ta industry-specifi applying to the as a whole. Wh semantic searc matching, or ot necessity of pro that include acc of risk is impera user trust in a s In addition to th anticipating mo vulnerabilities, t another challen whether or not a data is biased. large language as Transformers Even if one has art performance language proce benchmarks, or trained on datas from the edges internet. For exa dataset includes representations and other webs contain incendia that poison mod performance. T having definitive dataset creation the developmen data would ensu deployment of c datasets that pr and users can h confidence in. In order to solve challenges, a nu avenues can be Some apparent include: the dev use cases, unit team exercises challenges to id document the fu strategies to mi model risk. Prov community with opportunity to re the scenarios w go wrong could method to motiv add their voice problem. Howe

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						stands, there is central to test a objectively eval robustness for b explainability, e safety, and mor NIST is well pos develop an auth comprehensive identify and test vulnerabilities b deployment and forum to brainst spectrum of wh introduced in a then can risk m strategies be de ensure blind sp addressed in th development pi example of how identifies corner employs rigorou processes in the see the CVPR 2 Workshop on A Vehicles. The k continually upda test cases that a being proved or chances of succ increased when information can crowdsourced f around the worl vulnerabilities. (development of comprehensive Framework can across industrie define their poli see how they m field.
17						
18	2. How organizations currently define and manage characteristics of AI trustworthiness and whether there are important characteristics which should be considered in the Framework besides: accuracy, explainability and interpretability, reliability, privacy,		Corner Alliance, Inc.		Explaining and Harnessing Adversarial Examples (https://arxiv.org/pdf/1412.6572.pdf) Deep Fakes: A Looming Challenge for Privacy, Democracy, and National Security (https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3213954)	The "Explaining Harnessing Adv Examples" pape number of appli definitions, both included in the l terms and defin follows. Confidence: Wh neural networks decision is cong thought process Deterministic co (not logical ratio user has to be a both correct and decisions. Trust: When the making process have to be valid prediction safe

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robustness, safety, security (resilience), and mitigation of harmful bias, or harmful outcomes from misuse of the AI;					adopted? Adver diminish the val trait. Developec satisfactory test experience. Safety: Consist as expected. Gi its input, guard choices that ca impact the user Exhibit high reli both standard a exceptional ope conditions. Prov to a user about conditions influe decisions Ethics: Model d a code of moral defined by the u In addition to th on explainability Fakes: A Loomi for Privacy, Der National Securi provides a usef for risks related security implica fakes powered learning (ML). Deep Fakes de digital imperson leverages mach algorithms to in voices into vide recordings of ac and enables the realistic imperso digital whole clo deep fakes and forgeries more Amplifies cognit truth decay. Ena enhanced explo intimidation, an sabotage. Ther causes and cor this disruptive t change. Examples of MI Fakes: GANS (thispersondoes DeepMind's Wa Baidu's DeepVo commercial app Lyrebird. What are the ris fakes? Harm to Organization (E Sabotage); Har (Distortion of de

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						discourse; Man elections; Erodi institutions; Exa social divisions; public safety; U diplomacy; Jeo national securit Undermining jo
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20	3. How organizations currently define and manage principles of AI trustworthiness and whether there are important principles which should be considered in the Framework besides: transparency, fairness, and accountability;		Corner Alliance, Inc.		On the Dangers of Stochastic Parrots (https://dl.acm.org/doi/pdf/10.1145/3442188.3445922)	In Timnit Gebru Dangers of Stoc Parrots," the au at length the co that researchers aware of though and ML develop authors' main a that large AI mo showing better understanding, showing better of natural langu Therefore, the a the question: is pursue large mo considering the The authors the main drawbacks associated with namely environ financial costs, challenges, and of hegemonic w In terms of envi financial costs, underscores the energy efficient architectures ar paradigms, kno AI. Efficiency sh promoted as an metric in order t energy usage. compute used t largest deep lea has increased 3 (6) years, increa higher pace tha Law, according However, stand shape a future w driven systems negative impact environment. C Transformer wit architecture sea training emits 2 carbon dioxide. BERT on GPUs much energy as American flight. implore researc analyze the cos accuracy gain, example that fo

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					in 0.1 BLEU sc $150,000 for co plus carbon em encourage mor access to NLP reduce carbon authors recomm reporting trainin requirement. Ac urge governme compute clouds equitable acces researchers. Regarding train challenges, mo technology is b the needs of th already have th privilege in soci to the authors. data available c representative often not being systems. Rathe and derogatory are encoded al race, ethnicity, status. Large, u Internet-based encode the dominant/hege which further h the margins. Th recommend res allocation towa curation and do practices. They size of the data guarantee data Without a critic of dataset cont researchers ris dominant viewp increasing pow further reifying Furthermore, st do not reflect c views. A centra social moveme involves using strategically to dominant narra attention to und social perspect Therefore, thou practices to cap and techniques more frequently in dataset deve Additionally, mo encode bias if t datasets with s associations. T labeling males females as nurs

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					negative sentim specific ethnic g authors recomm out systems tha “safety” of a lan for a protected curation and do are key to acco dataset develop to curate and d better language training data, a oriented data c methodology sh developed. With documentation, cannot try to un training data ch fix issues. There researchers and should budget f documentation costs of project according to the Finally, in terms perpetuating he worldviews, Eng language mode exclusionary an risk degrading order to particip must subscribe hegemonic orde these models a While utterance in worldviews, p privilege are ov in the training d lead to framing dehumanizing v microaggressio become automa to reduce the ri producing and a automated bias technological e should be deve that evenly repr marginalized co worldwide. The authors co posing the prob the lens of com interest: the act choose today b amplified over t our best interes make choices t environment, co marginalized co and proper documentation/ Due to the fact be the benefits

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						disadvantages amplified over t important to ma choices now in compounded be
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22	4. The extent to which AI risks are incorporated into different organizations' overarching enterprise risk management – including, but not limited to, the management of risks related to cybersecurity, privacy, and safety;		Corner Alliance, Inc.		Explaining and Harnessing Adversarial Examples (https://arxiv.org/pdf/1412.6572.pdf) Switching Gradient Directions for Query-Efficient Black-Box Adversarial Attacks (https://arxiv.org/pdf/2009.07191.pdf) Switching Gradient Directions for Query-Efficient Black-Box Adversarial Attacks (https://arxiv.org/pdf/2009.07191.pdf) Adversarial Examples in Deep Learning Multivariate Time Series Regression (https://arxiv.org/abs/2009.11911)	Many organizat suited at incorp considerations i overarching ent management. M required on hov and test models mind. In particu for robustness a adversarial atta become more s practice. Advers are the major se to deep neural n (DNNs) that add imperceptible p benign images misclassificatio The following th provide valuabl about adversari could be incorp organizations' r management st The "Explaining Harnessing Adv Examples" pape overview of the training techniq describes how a change in an im to catastrophic misclassificatio defines an adve example as a p an image that re incorrect answe confidence. For vulnerability car picture of a pan classified as a g adding a small to the data. It su neural networks susceptible to a examples due t nature. To addre fundamental bli training algorith introduces a fas computing adve examples using weight optimiza technique. Alter suggests practi generate advers examples as th evaluate on tha does not solve

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					vulnerability to a examples, it do substantially re problem throug regularization b The "Switching Directions for Q Black-Box Adve Attacks" paper practitioners ca adversarial trai strengthen mod adversarial exa provides furthe how to use a m generate advers examples and t them in the trai Black-box attac realistic in real because they d the parameters of the target mo paper describe of black-box ad attacks, includi attacks and que attacks. The au a simple and hi efficient black-b attack named S at the time of pu state-of-the-art under L2 and L Transfer-based generate advers examples by at trained surroga fool the target n not require que target model. Q attacks require to the target mo based attack se accessing the lo value. Random- attacks use san random perturb iteration. Then, image is fed to model to compu value. The mod in the paper, ca bridges the gap transfer-based random-search- to improve the efficiency. The contribution is t proposed appro the gradient to the wrong direc consequently b potential obstac optimization, wh loss function in

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						much as possib Finally, the "Adv Examples in De Multivariate Tim Regression" pro example of how examples can a implemented in data. Multivaria (MTS) regressio in data mining a including financ cybersecurity, e healthcare, prog other areas. No learning is being solving MTS da problems, it is s and cost-critical these models d significant secu vulnerabilities. S learning algorith for their suscep adversarial exa work leverages adversarial atta techniques to cr adversarial MTS CNNs, LSTMs, This method wa on Google stock household powe consumption da paper's main fin the models are to adversarial a can lead to cata consequences. adversarial atta image domain i explored, this p contribution is t confirmation of across domains discussing pote techniques.
23						
24	5. Standards, frameworks, models, methodologies, tools, guidelines and best practices, and principles to identify, assess, prioritize, mitigate, or communicate AI risk and whether any currently meet the minimum attributes		Corner Alliance, Inc.		TextAttack: A Framework for Adversarial Attacks, Data Augmentation, and Adversarial Training in NLP (https://arxiv.org/pdf/2005.05909.pdf) Lessons learned in designing TextAttack (https://textattack.readthedocs.io/en/latest/1start/api-design-tips.html) Explainable Deep Learning: A Field Guide for the Uninitiated (https://arxiv.org/abs/2004.14545) CAM Paper (https://arxiv.org/pdf/1512.04150.pdf) Grad-CAM Paper (https://arxiv.org/pdf/1610.02391.pdf) Lottery Ticket Hypothesis (https://arxiv.org/pdf/1803.03635.pdf)	When it comes robustness, adv attacks can imp classification, e translation. "Tex Framework for A Attacks, Data A and Adversarial NLP" provides a how to develop how to utilize th model robustne allowing researc and study the e adversarial atta hopefully allow creation of user open-source NL

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described above;					that are more ro adversarial atta therefore ready distribution. The python library fo attacks and dat augmentation, a run via the com provides pre-tra for more than 8 datasets. It intro components of namely: creatin attacks through applying constra adversarial atta including transfo from adversaria literature; and u method. These be combined to adversarial atta "attack recipes. unites 15-plus p the NLP advers literature into a framework, then researchers to t the weaknesses models. TextAtt dozens of pre-tr (LSTM, CNN, a transformer-bas and supports ta summarization, translation, and from the GLUE Alternatively, in frameworks spe explainability, "E Deep Learning: for the Uninitiate thorough discus methods for exp neural networks methods it lists visualization me distillation; and methods. Visualization me highlight the cha that influence th DNNs. It answe question: to wha does a specific contribute to a d describes how t propagation to v feature relevanc volume of gradi through network network training examples of how in practice inclu

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					deconvolution, (CAM, layer-wis propagation, an perturbation. W deconvolution, i visualize higher in the input spa rectified linear f running a CNN CAM and Grad- class activation global average CNNs to indicat regions that we important to a n prediction for th is an approach which uses glob pooling on the l convolutional la in the soft max producing a hea indicate areas c for the network However, becau CAM is unable fully connected CAM is applical broader range c requiring that th activation functi the network pre differentiable fu CAM linearly cc importance sco feature map an through a ReLU relevance score relevance score up-sampled to b dimension as th to produce the c activation map. example of visu explainability is wise relevant pr which creates a to represent the each input featu output of the ne sensitivity metri the change in re network's outpu changing attribu input. The relev measures the s connection betv or pixel to the s network output. of layer-wise re propagation is D which assigns r scores to input based on the di between an inp reference input

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					Finally, perturba feature relevan comparing netw between an inp modified copy c compues input relevance by al removing the in and comparing in network outp the original and measures occlu sensitivity by co the image and s the model react Alternatively, in representation words are delet their absence ir prediction. Thes perturbations a predictors for a output, given ce These methods visualization us propagation to feature relevan the volume of g passed through layers during ne It is specifically image and text The downside c is the extra hum needed for verif is potentially co undesirable if a instant explana These visualiza could be very u identifying ratio many vision-ba The “Explainab Learning” pape describes meth distillation, whic “white-box” mac identifies the de input features. a post-training e methods where distilled into a r amenable for e a user. Distilled like a hypothesi DNN has assign class label to a way to achieve local approxima the practitioner simple model w input/output be that of a DNN f subset of input examples of loc

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					approximation, can look toward Interpretable M Explanations), a Shapley values analysis. Anoth achieve a distill through model t which the practi an alternative s that mimics the behavior of a D can be done to trees, finite stat graphs, and into rule-based mod example of succ distillation is the Hypothesis to fi trainable neural The final metho explainability pr “Explainable De paper is intrinsi which render ar along with the c can be done thr mechanisms, or training. Attentio mechanisms le key, value, quer learn conditiona over given inpu composing a we contextual vecto downstream pro attention visuali inherent explair training adds ar explanation “tas original model t jointly trains the task along with task. For examp mean a model u language proce explain how it a certain decision methods, while are promising a encourage expl the forefront of development. In addition to th listed above, th Deep Learning” provides details additional topics explainability. W methods or fran se, understandi topics relative to could help prac implement thes

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					their own mode these topics co stressed at eve educational opp related to expla These topics in learning mecha debugging, adv and defense, a and bias in DN The "Explainab Learning" pape the topic of lea mechanisms as explain the evol model's parame back propagatic this process, se meaning is assi weights and act Statistical patte convergence to state. This obse helpful to learn how layers evol training, how di converge, and i properties of ge and memorizati DNNs. The "Explainab Learning" pape describes mode as something li stethoscope, qu importance of s influential facto DNN's learning which some inf actively promot suppressed. Bo functions are us the state of the training. The same pape identifies adver and defenses a explainability. T intentionally dis judgement of a box attack occu attacker has no model paramet box attack occu parameters are avoid infiltration attacks, advers should be a crit component of n development a before deployin audiences.

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						Finally, “Explair Learning” devot to fairness and discussing diffe group fairness, fairness, demog and statistical p Emphasizing th of avoiding disp mistreatment, tl identifies three which analysis be conducted. F pre-processing, alternative repr the input data tl information corr sensitive attribu maintaining mo performance. S process of train practitioner sho introduce fairne constraints to th order to punish decisions and a fairness regular during post-proc hoc fairness pro trained model to deployability.
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26	6. How current regulatory or regulatory reporting requirements (e.g., local, state, national, international) relate to the use of AI standards, frameworks, models, methodologies, tools, guidelines and best practices, and principles;				N/A	N/A
27						
28	7. AI risk management standards, frameworks, models, methodologies, tools, guidelines and best practices, principles, and practices which NIST should consider to ensure that the AI RMF aligns		Corner Alliance, Inc.		Explainable Deep Learning (https://arxiv.org/abs/2004.14545)	The “Explainab Learning” pape number of user explanations fo developing mod User experienc Practitioners sh think: Who is th How practically the decisions o How “extendab explanation? Understanding Low level techn

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	with and supports other efforts;					explanations (ir analytics; hidde interactions); Hi explanations fo people (functior model; logical r The Impact of D Decisions: Time driving cars; mil operations); De (medical diagno Design Extenda reaching can th of these model be? How will thi lifecycle of a mo implementing e mechanisms m in models lead become more r Improve ROI of
29						
30	8. How organizations take into account benefits and issues related to inclusiveness in AI design, development, use and evaluation – and how AI design and development may be carried out in a way that reduces or manages the risk of potential negative impact on individuals, groups, and society.		Corner Alliance, Inc.		OECD: Principles on AI (https://legalinstruments.oecd.org/en/instruments/OECD-LEGAL-0449)	The OECD: Prir provides a usef on how benefits carried out in a reduces negativ society. Key poi follows: Inclusive growth development, a Beneficial outco people and the as augmenting capabilities and creativity, advar of underreprese populations, rec inequalities, and natural environ Human-centere fairness: Respe law, human righ democratic valu freedom, dignity privacy, and dat equality, fairnes justice, and labo Safeguards sho implemented in situations, such human in the lo Transparency a Explainability: A disclose meanir information to h stakeholders ur interactions witl outcomes were Robustness, Se

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						Safety: AI shoul unnecessary ris should be trace regarding datas processes, how prior decisions s outcomes can b Actors should a systematic risk approaches for security, strateg Accountability: A be accountable functioning of A
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32	9. The appropriateness of the attributes NIST has developed for the AI Risk Management Framework. (See above, "AI RMF Development and Attributes");				N/A	N/A
33						
34	10. Effective ways to structure the Framework to achieve the desired goals, including, but not limited to, integrating AI risk management processes with organizational processes for developing products and services for better outcomes in terms of trustworthiness and management of AI risks. Respondents are asked to identify any current models which would be effective. These could include – but are not limited to – the NIST Cybersecurity Framework or Privacy				N/A	N/A

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	Framework, which focus on outcomes, functions, categories and subcategories and also offer options for developing profiles reflecting current and desired approaches as well as tiers to describe degree of framework implementation; and					
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36	11. How the Framework could be developed to advance the recruitment, hiring, development, and retention of a knowledgeable and skilled workforce necessary to perform AI-related functions within organizations.				N/A	N/A
37						
38	12. The extent to which the Framework should include governance issues, including but not limited to make up of design and development teams, monitoring and evaluation, and grievance and redress.		Corner Alliance, Inc.		Common Code (https://www.cnas.org/publications/reports/common-code)	Governance sh consideration to unified policies management. E consistent proc design and dev teams, monitori evaluation, and ensure a minim requirements a of impact, scop resources. The Center for American Secu Code report pro number of reco to consider whe governance co for technology p recommendatio for the develop Risk Managem include: Collaborating W

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					Countries Adopting A Voti Engaging With Stakeholders Establishing Me Structure And F Craft Standards For A Beneficial Future These recomme others listed in t could be useful the structure, or and methods er the Framework develop teams.
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