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Efficient and reliable AI systems should be designed according to the best general practices for software systems, along with practices that address unique considerations for machine learning. Our main recommendations are described below, with additional resources for further readings. The way real users experience the system is essential to assess the true impact of its forecasts, recommendations and decisions. Design features with its integrated information: clarity and control is essential for a good user experience. Consider the increase and assistance: producing a single response can be appropriate if there is a high probability that the response meets a diversity of users and usage cases. In other cases, it can be optimal for the system to suggest some options to the user. Technically, it is much more difficult to get a good accuracy at one answer (P@1) against accuracy to a few answers (e.g., P@3.) Potential feedback model early in the design process, followed by specific live tests and iteration for a small fraction of traffic before full distribution. Involve with a diverse range of users and usage scenarios, and incorporate feedback before and during project development. This will build a rich variety of perspectives for project users and increase the number of people who benefit from technology. Using different metrics rather than a single will help you understand the tradeoffs between different types of errors andConsider metrics, including feedback from user surveys, quantities that track overall system performance and product heath short and long term (e.g. click-through rate and customer life value respectively), and false positive and false negative rates sliced into different subgroups. Make sure metrics are appropriate for the context and system objectives, for example, a fire alarm system should have a high call, although this means the false occasional alarm. ML models will reflect the data on which they are formed, so carefully analyze your raw data to ensure you understand it. In cases where this is not possible, for example, with sensitive raw data, understand the input data as much as possible in respect of privacy; for example by means of computer aggregates, anonymized synthesis. Does your data contain errors (for example, missing values, incorrect labels)? Your data is sampled in a way that represents your users (for example, they will be used for all ages, but you only have training data from the elderly) and setting the real world (for example, it will be used all year round, but you only have training data from the summer)? Is the data accurate? The difference between performance during training and performance during service is a persistent challenge. During training, try to identify potential spies and work to address them, even by adjusting training data or objective function. During the evaluation, continue to try to get the evaluation data that is asas much as possible of the unfolded setting. are the features of your model redundant or useless? use the simplest model that meets your performance goals. for supervised systems, consider the relationship between the data labels you have, and the elements you are trying to predict. if you use a x data label as a proxy to predict a y label, in which cases is the gap between x and y problematic? data prejudice is another important consideration; learn more about artificial intelligence and equity practices. a model trained to detect correlations should not be oato to make causal inferences, or imply that it can. For example, your model can learn that people who buy basketball shoes are higher on average, but this does not mean that a user who buys basketball shoes will become higher accordingly. automatic learning models today are largely a reflection of the models of their training data. It is therefore important to communicate the scope and coverage of the training, so clarify the capacity and limitations of the models. For example, a shoe detector trained with stock photos can work better with stock photos but has a limited capacity when tested with user-generated cell phone photos. communicate restrictions to users if possible. For example, an application that uses ml to recognize specific species of birds could communicate that the model was trained on a small set of images from a specific region of the world. improving your education, you can also improve the feedback provided by users on your function orLearn from software engineering best quality testing and engineering practices to make sure the AI system is working as expected and can be trusted. Conduct stringent drive tests to test each component of the system in isolation. Conduct integration tests to understand how individual ML components interact with other parts of the general system. Proactively detect the input drift by testing input statistics to the AI system to make sure they are not changing in unexpected ways. Use a standard gold data set to test the system and make sure it continues to behave as expected. Update this test set regularly in line with evolving users and usage cases, and to reduce the probability of training on the test set. Conduct iterative user testing to incorporate a diverse range of user needs in development cycles. Apply poka-yoke quality engineering principle: build quality controls in a system, so that undesirable failures can not happen or trigger an immediate response (for example, if an important feature is unexpectedly missing, the AI system does not issue a prediction). Continuous monitoring will ensure that the model takes into account the real world performance and user feedback (e.g., happiness monitoring surveys, the HEART framework). Problems will occur: any model of the world is imperfect almost by definition. Build time in the product roadmap to allow you to deal with problems. Consider both short and long-term solutions to problems. A simple solution (for example, blacklisting orcan help you solve a problem quickly, but it may not be the optimal solution in the long term. Short-term balance simple corrections with long-term solutions learned. Before upgrading a distributed model, analyzing how the candidate and the deployed models differ, and how the update will affect the general quality of the system and user experience. AI Manager with TensorFlow A consolidated toolkit for third-party developers on TensorFlow to build ML accuracy, interpretability, privacy and security in their models. Colab tools and tutorials to help model developers exploit Machine Learning MetaData (MLMD) to build template cards. A practical guide that outlines the best practices for ML engineering. Recommended steps to stay focused on the user by our Google UX community. Learning the machine: the high interest credit card of the technical debt ML-specific risk factors and design patterns for refactor or avoid. Communicates how Google's search algorithm works and helps webmasters understand quality and ranking. The People + AI Research initiative publishes practical insights into multidisciplinary and man-centered approaches to design with AI. AI systems are enabling new experiences and skills for people around the world. In addition to recommending books and television programs, AI systems can be used for more critical tasks, such as predicting the presence and severity of a medical condition, matching people to jobs and partners, or identifying if a person is crossing the road.The IT systems of assistance or decision-making have the potential to be fairer and more inclusive in a broader scale than decision-making processes based on ad hoc rules or human judgments. The risk is that any unfairness in such systems can also have a large scale impact. Thus, as the impact of AI increases in sectors and societies, it is essential to work towards systems that are fair and included for all. This is a difficult task. First, ML models learn from existing data collected from the real world, and therefore an accurate model can learn or even amplify the pre-existing problematic biases in race-based, gender, religion or other characteristics. For example, a work-matching system could learn to favor male candidates for CEO interviews, or hire female pronouns when translating words like "nurse" or "babysitter" in Spanish, because this corresponds to historical data. Secondly, even with the most rigorous and transversal training and testing, it is a challenge to ensure that a system will be fair in all situations. For example, a voice recognition system that has been trained to American adults can be fair and inclusive in that context. When used by adolescents, however, the system may not recognize the words or phrases in evolving slang. If the system is distributed in the UK, it may have a more difficult time with some British regional accents of others. And even when the system is applied to American adults, we could discover unexpected segments of the populationThe speech is bad, for example people who speak with a stutter. The use of the system after the launch can prove unwilling, the unjust blind points that were difficult to predict. Thirdly, there is no standard definition of correctness if decisions are made by humans or machines. Identifying appropriate correctness criteria for a system requires an accounting for user experience, cultural, social, historical, political, legal and ethical considerations, many of which may have tradeoffs. Is it more right to give loans at the same rate to two different groups, even if they have different payback rates, or is it more right to give proportional loans to the repayment rates of each group? Is none of these the right approach? At what level of granularity should groups be defined, and how should the boundaries between groups be determined? When is it right to define a group at all against a better factor on individual differences? Even for situations that seem simple, people may not agree on what is right, and it may be unclear what point of view should dictate politics, especially in a global context. Referring to equity and inclusion in AI is an active area of research, from the promotion of an inclusive workforce that embodies critical and diversified knowledge, to the evaluation of training datasets for potential sources of prejudice, to the training of models to remove or correct problematic prejudices, to the evaluation of machine learning models for performance disparities, to the continuous experimentation of final systems toresults. In fact, the ml models can also be used to identify some of the conscious and unconscious human prejudices and barriers to inclusion that have developed and perpetuated throughout history, leading to positive changes. far from a solved problem, the equity in ais presents both an opportunity and a challenge. google is committed to making progress in all these areas, and creating tools, data sets and other resources for the larger community. our current thought at google is described below. It is important to identify if machine learning can help provide a solution to the specific problem at hand. if it can, just as there is no single “correct” model for all ml activities, there is not only one technique that guarantees equity in every situation. In practice, researchers and developers should consider using a variety of approaches to iterate and improve. engage with social scientists, humanists and other experts relevant to your product to understand and take into account various perspectives. to consider how technology and its development over time will affect different usage cases: who are the opinions represented? What types of data are represented? What was left out? what results allows this technology and how do they compare for different users and communities? What prejudices, negative experiences or discriminatory results could occur? set the goals for the system to work enough in cases of intended use: for example, in x different languages,a Y different age groups. Monitor these goals over time and expand as appropriate. Design your algorithms and objective function to reflect goals of correctness. Update your training and testing data frequently based on who uses your technology and how they use it. Evaluate the equity in your data sets, which includes the identification of the representation and the corresponding limits, as well as the identification of biased or discriminatory correlations between characteristics, labels and groups. Viewing, clustering and data annotations can help with this rating. Public training datasets will often have to be upgraded to better reflect the real world frequencies of people, events and attributes that the system will make forecasts about. Understand the various perspectives, experiences and goals of people who announce data. What is the success for different workers, and what are the trade-offs between the time spent for the task and enjoyment of the task? If you work with annotation teams, collaborate closely with them to design clear tasks, incentives and feedback mechanisms that guarantee sustainable, diverse and accurate annotations. Account for human variability, including accessibility, muscle memory, and annotation biases, for example, using a standard set of questions with known responses. For example, organize a trustworthy and different tester pool that can test the system transversely, and incorporate a variety of opponent inputs into unit testing. This can help identify whoexperience unexpected adverse impacts. Even a low error rate can allow very bad occasional error. Targeted opponent tests can help you find problems masked by aggregated metrics. While designing metrics to form and evaluate the system, they also include metrics to examine performance in different subgroups. For example, the false positive rate and the fake negative rate for subgroups can help you understand which groups experience disproportionately worse or better performance. In addition to slicing statistics metrics, create a set of tests that stress-test system on difficult cases. This will allow you to quickly assess how your system is doing on examples that can be particularly bad or problematic whenever you update the system. As with all test sets, you need to constantly update this set while the system evolves, features are added or removed and you have more feedback from users. Consider the effects of biases created by the decisions taken by the system earlier, and feedback loops that this can create. Take the different metrics you have defined in consideration. For example, a false positive rate of a system may vary in different subgroups in your data, and improvements in one metric may adversely affect another. Evaluate user experience in real scenarios through a broad spectrum of users, usage cases and usage contexts (e.g., TensorFlow model analysis). Test and iterate in dog food before, followed by a continuous test after launch. Even thoughin the general design of the system is carefully designed to deal with correctness issues, ML-based models rarely work with 100% perfection when applied to real and live data. When a problem occurs in a live product, consider whether it aligns with any existing social disadvantages, and how it will be influenced by solutions both short and long term. Gender-specific translations into Google Translate Females and male translations for some gender-neutral words on Google Translate's website, to help reduce gender bias in translations. Ensure equity in ML to anticipate health equity Overview of interaction between ML correctness and health inequalities. Provides a tool for anyone to help form Google AI; the goal is to generate training data and large, open data sets that represent the diversity of cultures from all over the world Create an open data set that collects statements other than LGBTIQ+ and other marginalized communities, to detect and address unfair bias in the ML Geena Davis Inclusion Quotient uses modern computer word and vision techniques to analyze and document the sub-representation of women in the film. A competition for the global community of developers and research to form vision models that work equally well for a globally diverse set of images An open data set to help expand the diversity of cultures and people represented in ML Fairness Gym (open source) image training data A set of components for building simple simulations that explore potentialimpacts of implementing decision-making systems based on machine learning in social environments. Tenor Flow Model Repair Library A library to help ML developers improve the performance of their models in all data parts. One way to share executable code, including different machine learning techniques for correctness. A library that promotes the publication, discovery and consumption of ML models so that more people can access technology. A tool for displaying, analyzing and understanding of the dataset composition. Tenor Analysis of flow model A library for processing flaws and full-pass metrics. Released metrics allow model performance analysis for specific subgroups to help identify biases in data or model forecasts. An interactive tool built in TensorBoard, and used in Jupyter and Colaborator notebooks, to analyze model performance on a data set; allows users to view biases and effects of various correctness constraints and compare performance between multiple models. A library that implements lattice (such as TensorFlow Estimators or modular layers;) these are fast, flexible and interpretable models that provide a rich set of semantic regularizers. Particularly useful for monotonity and to manage biased data. Correction indicators is a tool built on the top of Tensorflow Model Analysis that allows regular calculation and display of correctness metrics for binary and multi-class classification. Open educational resources so that more people can learn and developThe Intro to Fairness module teaches users about higher accuracy considerations when building, evaluating and distributing machine learning models. Provides an inclusive ML guide to help users understand, detect and address unfair prejudices in their training data and custom models. Machine learning equity: Learn lessons Explore Google's techniques and resources that allow improvements to models, including open source data sets and tools. Write the game folder for ethical artificial intelligence and MML Learn from Googlers who are implementing a robust picture for ethical artificial intelligence, and ensure that Google products do not amplify or propagate unjust prejudices. Automated predictions and decision-making can improve life in many ways, from advising the music you might want to monitor the vital signs of a patient. Interpretability is fundamental to be able to question, understand and trust AI systems. Interpretability also reflects our knowledge of domain and social values, provides scientists and engineers with the best means of design, development and debugging models, and helps ensure that AI systems function as expected. These questions apply to human beings and AI systems, after all, it is not always easy for a person to provide a satisfactory explanation of their decisions. For example, it can be difficult for an oncologist to quantify all the reasons why they think that a patient's cancer can be redeemed – they can only say they have an intuition, leading them to ordertests for more definitive results. On the contrary, an AI system can list a variety of information that went in its forecast: Biomarker levels and corresponding scans from 100 different patients over the past 10 years, but they have a difficult time communicating how it combined all those data to estimate a 80%% chance of cancer and recommendation to get PET scan. Understanding complex AI models, such as deep neural networks, can also be difficult for machine learning experts. Understanding and testing AI systems also offers new challenges compared to traditional software. Traditional software is essentially a set of rules if-then, and interpreting and debugging performance largely consists of chasing a problem down a garden of forking paths. While this can be gnarly, a human can generally follow the path taken through the code, and understand a given result. With AI systems, the "code path" can include millions of parameters and mathematical operations, and it is much more difficult to identify a specific bug that leads to a faulty decision. However, with a good design of the AI system, these millions of values can be traced back to the training data or to model attention on specific data or features, resulting in the discovery of the bug. This contrasts with one of the key problems of traditional decision-making software, which is the existence of “magic numbers”, rules of decision or thresholds established without explanation by a programmer now forgotten, often based on their personal intuitiona small series of test examples. Overall, an AI system is better understood by the underlying training process and training, as well as the resulting AI model. While this poses new challenges, the collective effort of the technological community to formulate guidelines, best practices and tools is constantly improving our ability to understand, control and debug AI systems. It is an area of intense research and development to Google, and we would like to share some of our current works and think in this area. While a complete solution for interpretation and responsibility is an active area of research on Google and in the ML community, here we share some of our recommended practices until today. The interpretation can take place before, during and after the design and formation of the model. What degree of interpreters do you really need? Work closely with domain experts relevant to your model (e.g., healthcare, retail, etc.) to identify which interpretation functions are necessary, and why. Although rare, there are some cases/systems where with sufficient empirical evidence, the interpretability of the fine grain is not necessary. Can you analyze your training/testing data? For example, if you work with private data, you cannot have access to investigate input data. Can you change your training/testing data, for example, collect more training data for some subsets (for example, parts/slice of the functional space), or collect test data for interest categories? You can design a new model orYou've been tied to an already trained model? Are you providing too much transparency, potentially opening carriers for abuse? What are your post-train interpretation options? Do you have access to the interior of the model (for example, black box vs white box)? Design with users in the development cycle to test and refine your assumptions on user needs and goals. Design the U.S. so users build useful mental models of the AI system. If you do not give clear and convincing information, users can invent their own theories on how an AI system works, which can negatively affect how they try to use the system. If possible, make it easy for users to do their own sensitivity analysis: allow them to test how different inputs affect the output of the model. Other relevant UX resources: Design of human needs, user control, teaching an AI, habit, correctness, representation Use the smallest set of inputs needed for your performance goals to make clear what factors are affecting the model. Use the simplest model that meets your performance goals. Learn causal relationships not correlations when possible (for example, use height not age to predict if a child is safe to drive a roller coaster). Put the training goal to match your true goal (for example, form for the acceptable probability of false alarms, not accuracy). Mark your model to produce input-output reports that reflect expert domain knowledge (for example, a coffee shop should be more likely to be recommendedis closer to the user, if everything else is the same). The metrics you consider must face the particular advantages and risks of your specific context. For example, a fire alarm system would need a high call, although this means the occasional false alarm. Many techniques have been developed to obtain model information (e.g., input sensitivity). Analyze the sensitivity of the model to different inputs, for different subsets of examples. Provide explanations that are understandable and appropriate for the user (for example, technical details can be appropriate for industry professionals and academy, while general users can find user interface requests, synthesis descriptions or more useful views). The explanations must be informed by careful consideration of philosophy, psychological, computer science (including HCI), legal and ethical considerations on what counts as a good explanation in different contexts. Identify if and when explanations may not be appropriate (for example, when explanations may cause greater confusion for general users, nefarious actors may take advantage of the explanation for the system or user abuse, or explanations may reveal proprietary information). Consider alternatives if explanations are required by a certain user base, but cannot or should not be provided, or if you cannot provide a clear and solid explanation. You could instead provide responsibility through other mechanisms such as auditing or allowingto contest decisions or provide feedback to influence future decisions or experiences. Priorize explanations that suggest clear actions that a user can take to correct inaccurate forecasts in progress. Do not imply that explanations mean causality unless they do. Recognize psychology and human limits (for example, confirmation bias, cognitive fatigue) Explanations can come in many forms (e.g. text, charts, statistics): when using the display to provide insights, use the best practices from HCI and display. Any aggregated summary may lose information and hide details (e.g., partial dependency charts). The ability to understand the parts of the ML system (especially inputs) and how all parts work together (“completeness”) helps users build clearer mental models of the system. These mental models correspond to the performance of the real system more closely, providing a more reliable experience and more accurate expectations for future learning. Be aware of the limits of your explanations (for example, local explanations cannot generalize in general, and can provide contrasting explanations of two visually similar examples). Learn from software engineering best quality testing and engineering practices to make sure the AI system is working as expected and can be trusted. Conduct stringent drive tests to test each component of the system in isolation. Proactively detect the input drift by testing input statistics to the AI system to make sure they are not changing inways. Use a standard gold data set to test the system and make sure it continues to behave as expected. Update this test set regularly in line with evolving users and usage cases, and to reduce the probability of training on the test set. Conduct iterative user testing to incorporate a diverse range of user needs in development cycles. Apply poka-yoke quality engineering principle: build quality controls in a system so that undesired failures can not happen or trigger an immediate response (for example, if an important feature is unexpectedly missing, the AI system will not issue a prediction). Conduct integration tests: understand how the AI system interacts with other systems and what, if there is, feedback loops are created (for example, advising a story of news because it is popular can make that story of news more popular, causing its recommendation more). A tool for displaying, analyzing and understanding of the dataset composition. An exploratory data analysis tool that explicitly seeks both statistical majors and minorities in data. The Google Cloud Tools and framework can be explained to help develop interpretable and inclusive machine learning models and deploy them with confidence, including the guide on known limitations. Tenor Flow Lattice (open source) Pre-constructed stimulators that allow training models to acquire prior knowledge about whether an input can or should only have a monotonous effect on an output. For example, the entry "time last cleanbathroom" should only have a positive impact on the predicted probability that “it's time to clean that bathroom again.” It examines the use of classification constraints during training to increase responsibility, including the attainment of correctness metrics between groups and ensure the correct decision-making process of ranking on key examples. Interpretability in medical applications A model trained on medical records of electronic health that explains its forecasts highlighting the relevant data in the patient's table. Interpretability of disease prediction Model ML developed for the identification of chest disease in radiology images, with location of abnormal areas for interpretation. Towards a rigorous science of interpretable machine learning Tips on when interpretation is necessary (and when it is not), and a taxonomy for a rigorous evaluation of interpretable machine learning. Human-in-loop Interpretability Prior It is a framework to learn a more interpretable model for the final game by asking humans which models are more interpretable during the formation of the model. The ML models learn from the training data and forecast input data. Sometimes training data, input data, or both can be quite sensitive. Although there may be enormous advantages for building a model that operates on sensitive data (for example, a cancer detector trained on a set of biopsy image data and distributed on individual patient scans), it is essential to consider potential privacy implications in usedata. This includes not only compliance with legal and regulatory requirements, but also the consideration of the social norms and individual expectations. For example, what guarantees must be made to ensure the privacy of people considering that ML models can remember or reveal aspects of the data to which they were exposed? What steps are needed to ensure that users have sufficient transparency and control of their data? Fortunately, the possibility that ML models reveal the underlying data can be minimized by applying appropriately various techniques in a precise and basic way. Google is constantly developing such techniques to protect privacy in AI systems. It is a continuous research area in the ML community with a significant space for growth. Below we share the lessons we have learned so far. Just as there is no single “correct” model for all ML activities, there is no only one correct approach to protecting ML privacy in all scenarios. In practice, researchers and developers must try to find an approach that adequately balances privacy and utility for the task at hand; for this successful process, a clear definition of privacy is necessary, which can be both intuitive and formally accurate. Identify whether the ML model can be trained without the use of sensitive data, for example, using nonsensical data collection or an existing public data source. If it is essential to process sensitive training data, strive to minimize the use of such data. Maneggiare anydata with care: for example, comply with the laws and standards required, provide users with clear communication and give them the necessary controls on data usage, follow the best practices such as encryption in transit and rest, and comply with Google's privacy principles. Anonymize and aggregate incoming data using the best data-scrubbing pipeline practices: for example, consider removing identifiable personal data (PII) and outlier or metadata values that may allow de-anonymization (including implicit metadata such as the order of arrival, removable by random shuffling, as in Prochlo; or the API Cloud Data Loss Prevention to automatically discover and redeem sensitive and identifiable data). If your goal is to learn individual interaction statistics (e.g. how often some user interface elements are used), consider collecting only statistics that have been locally calculated, on-device, rather than raw interaction data, which may include sensitive information. Considering whether techniques such as federated learning, where a fleet of devices coordinates to form a global model shared by locally-stored training data, can improve privacy in the system. When possible, apply aggregation, randomization and on-device scrubbing operations (for example, secure aggregation, RAPPOR and Prochlo coding phase). Note that these operations can only provide pragmatic privacy and greater comfort unless the techniques used are accompanied by evidence. Why ML models can expose details about their training data both through their interiorAs well as their external-visible behavior, it is essential to consider the impact on privacy of how models have been built and can be accessible. Evaluate whether your model is involuntarily storing or exposing sensitive data using “exhibit” measurement tests or registration evaluation. These metrics can also be used for regression testing during model maintenance. Experiment with data minimization parameters (e.g., aggregation, higher thresholds and randomization factors) to understand tradeoffs and identify the optimal settings for your model. Form ML models using techniques that establish mathematical safeguards for privacy. Note that these analytical guarantees are not guarantees about the complete operating system. Follow best practice processes established for cryptographic and critical security software, such as the use of principle and testable approaches, peer-reviewed publication of new ideas, open-sourcing of critical software components, and the inclusion of experts for review in all stages of design and development. Mechanism for large-scale data collection with strong local differential protection guarantees. Followed to RAPPOR; The Encode-Shuffle-Analyze architecture offers a better utility and anonymity. It serves as the basis of Cobalt in the Google Fuschia open-source project. Method to form ML models using data that never leave a user device. This technology is used to form smart functions in Gboard toand on google pixel devices. federated learning can also use a user's data to allow custom on-device models. flow federated (open source) a framework for machine learning and other calculations on decentralized data, developed to facilitate open research and experimentation with federated learning and related technologies. Safe aggregation protocol provides strong cryptographic privacy for individual user updates in a federated learning model, mediating only updates from large groups of participants. a related technique can be used to attribute conversions to aggregates. These are techniques to evaluate when the ml models are unintentionally memorizing and potentially exhibiting sensitive data aspects, and to change the pattern training regime to ensure that such details cannot be stored first. tensorflow privacy (open source) practical techniques to form deep networks with differential privacy at a manageable cost. the accounting technique of the moments of this work can be used for model analysis. measurement of unwanted neural network memory and extraction of secrets a easily applicable exposure metric to evaluate unintended storage of the secret data model ml. This technique can be used during model development and during model maintenance (for example, in regression tests,) and the results of this research have recently been used during the development of smart composites in gmail. learning patterns of recurring language differentially private demonstratesto form large recurring language models with differential user-level privacy guarantees, with a negligible cost in predictive accuracy. a decentralized ml model training process with apparent and intuitive privacy, as well as a strong and differentiated mathematical privacy, guarantees security and security involves the security of systems to, regardless of how attackers try to interfere. It is essential to consider and address the security of a system to the first that it is widely used in critical security applications. There are many unique challenges for system security to. For example, it is difficult to predict all scenarios in advance, especially when ml is applied to problems that are difficult for humans to solve. It is also difficult to build systems that provide both the necessary security restrictions and the flexibility needed to generate creative solutions or adapt to unusual inputs. while technology develops, attackers will surely find new means of attack; and new solutions must be developed in tandem. Below are our current recommendations from what we have learned so far. ml security research embraces a wide range of threats, including the poisoning of training data, the recovery of sensitive training data, theft of models and adversaries. google invests in research related to all these sectors, and some of this work is related to practices in privacy and privacy. a focus on safety researchGoogle was the opponent's learning — the use of a neural network to generate opposing examples that can deceive a system, coupled with a second network to try to detect fraud. Currently, the best defenses against opponents are not yet reliable enough for use in a production environment. It is a continuous and extremely active research area. Since there is still no effective defense, developers should think if their system is likely to come under attack, consider the likely consequences of a successful attack and in most cases should not simply build systems where such attacks are likely to have a significant negative impact. Consider if someone would have an incentive to make the system bad. For example, if a developer builds an app that helps a user to organize their photos, it would be easy for users to edit photos to organize incorrectly, but users can have limited incentives to do so. Identify what consequences would result from the system to make a mistake, and assess the probability and severity of these consequences. Build a strict threat model to understand all possible attack vectors. For example, a system that would allow an attacker to change entry to the ML model can be much more vulnerable than a system that processes metadata collected from the server, as timestamps of actions that the user took, since it is much more difficult for a user to intentionally change the input features collected without their directSome applications, for example, spam filtering, can be successful with current defense techniques despite the difficulty of an opposing character. Test the performance of your systems in the opposing setting. In some cases this can be done using tools like CleverHans. Create an internal red team to test, or host a contest or a bounty program that encourages third parties to test the system in a cross-check. Stay up to date on the latest research progress. Research into learning opposing machines continues to offer better performance for defenses and some defense techniques are beginning to offer proveable guarantees. In addition to interfering with input, there may be other vulnerabilities in the ML supply chain. While this attack has not yet happened for our knowledge, it is important to consider the possibility and be prepared. CAT-Gen: Improve robustness in NLP models through controlled opposing text generation Controlled Adversarial Text Generation (CAT-Gen) is a model that, given an input text, generates opposing texts through controllable attributes that are known to be invariant to task labels. Our method can generate more different and fluent opposing texts, compared to many existing generation approaches. We use our generated adversary examples to improve models through adversary training, and we show that our generated attacks are more robust against model re-forming and different model architectures. EvaluationRobustness Overview of methodological bases and best practices and methods to evaluate defenses to opposing examples. Ensemble Opponent Training Discover defenses against the opposing examples of black-box, developed in collaboration with Stanford. A safety research library for the learning of open source machines. A 2017 Google-led contest on Kaggle Google was one of the groups to independently discover adversaries, including the development of opponents training in 2013. This technique is now the basis for the state of the defenses of art. A collaboration with Stanford, UC Berkeley and OpenAI for basic issues in machine learning security research, and outlines practical approaches to safe and reliable AI systems. Challenge of opposing examples without restrictions A competition created to encourage search in the construction of systems that never make safe errors on simple tasks. tasks.

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