OpenDP Privacy Attacks & Auditi	ng Working Group										
Privacy Attacks Respository											
URL	BibTex (Please add a bibtex entry for this paper to facilitate writing our summary document)	Authors	Title	Short Description	Type of Data	Type of Release	Threat Model	Research Type	Links to Artifacts	Comments	Submitter (your name, affiliation)
https://dl.acm.org/dol/10_ 1145/773153.773173	@inproceedings[10.1145/773153.773173, author = (Dinur, Irit and Nissim, Kobbi), Ittle = (Revealing information while preserving privacy), year = (2003), }	Irit Dinur and Kobbi Nissim	Revealing Information While Preserving Privacy	Seminal paper on the theory of data reconstruction attacks.	Tabular	Linear-Queries	Reconstruction	Theoretical			Jon Ullman, Northeastern University
https://anxiv.org/abs/1810.05692	() garticle(cohen2018linear, title=(Linear program reconstruction in practice), author=(Cohen, Aloni and Nissim, Kobbi), year=(2018)	Aloni Cohen and Kobbi Nissim	Linear program reconstruction in practice.	Implemented linear reconstruction attacks against a production private query system called Diffix	Tabular	Linear-Queries	Reconstruction	Applications			Jon Ullman, Northeastern University
https://arxiv.org/abs/2405.10994	verticel panamska2024you, totles-(* What do you want from theory alone?" Experimenting with Tipot Auditing of Differentially Private Synthetic Data Generation), author-(Annamal), Meentath Saudaram Muthu Selva and Ganeo, Georgi and De Cristofano, Emiliano), journal-(USENK Southy), year-(2024)	Meenatchi Sundaram Muthu Selva Annamalai, Georgi Ganev, Emiliano De Cristofaro	"What do you want from theory alone?" Experimenting with Tight Auditing of Differentially Private Synthetic Data Generation	Audits six implementations of DP synthetic data generative models using different datasets and threat models and finds that commonly used black- box MIAs are severely limited in power, yielding remarkably loose empirical privacy estimates. Considers MIAs in stronger threat models, i.e., pastive and active white-box, using both existing and newly proposed attacks.	Tabular	Generative-Model	Membership-Inference	Empirical	https://github, com/spalabucr/synt h-audit		Georgi Ganev, UCL
https://broceedings.neurips. ccbaper/2020/Ke/EddcL15/9/4b 4b06cr/7844d6bb53abf-Paper, pdf	(Jarticle[jagielsk2020auditing, title=/Laditing differentially private machine learning How private is private (SGD)?), author-[Jagielski, Matthew and Uliman, Jonathan and Oprea, Alina), journai-(Advances in Neural Information Processing Systems),	Matthew Jagielski, Jonathan Uilman, Alina Oprea	Auditing Differentially Private Machine Learning: How Private is Private SGD?	Connects the success rate of a membership inferency adversary to a lower bound on the privacy loss of the underlying DP mechanism.	Image	Predictive-Model	Membership-Inference	Empirical			Tudor Cebere, Inria
https://www.pass.org/doi/10. 1072/page.2218606120	Sensel 2022andralona, Sensel 2022andralona, Sensel 2022andralona, Sensel 2022andralona, Sensel 2024andralona, Sensel 2024andralona, Sensel 2024andralona, Sensel 2024andralona, Sensel,	Travis Dick, Cynthia Dwork, Michael Kearns, Terrance Liu, Aaron Roth, Glucoppe Vietr, and Zhwei Szeven Wa	Confidence-ranked reconstruction of concurs microdula frompublished statistics	Ranking rows in reconstructed microdata by how confident the adversary is that are in the true dataset.	Tabular	Linear-Queries	Membership-Inference	Empirical		I didn't want to give it it's own row but linking a rebuttal paper which is interesting in that it is indicative of arguments people make against reconstruction attacks: pittes Barek combes/2311, 03121	Audra McMillan, Appla
http://diamorphol/abs/10_ 1145/3546666 3560581	(ii) inproceedings[crist2022]auvyrnoid; Har-Qiovyrñou: Automating the discovery of Har-Qiovyrñou: Automating the discovery of systems], autor-(Crista, harvina and Hossiaia, Enrinned and Calify, Antoine and de Morginey, two: Alexandro, Loottae-(Proceedings of the 2022 ACM SGSAC Conference) and Campater and Communications pages=(1022) year=(2022)	Ana-Maria Cretu, Florimond Hourslau, Antoine Cully, Wes-Alexandre de Montjoye	QuerySnout: Automating the Discovery of Attribute Inference Attacks against Query-Based Systems	A method to automatically discover attacks against interactive query systems	Tabular	Linear-Queries	Attribute-Inference	Empirical			Ana-Maria Cretu, EPFL
https://www.ndss-symposium. org/wp- content/uploads/2018/02/ndss20 18_058-5_Pvrgelis_paper.pdf	(anticlefyrgelis2017/nock, title={Knock knock, who's there? Membership inference on aggregate location data), author={Prygelis, Apostolos and Tronceso, Carmela and De Cristoface, Emiliano), journal={arXiv preprint arXiv:1708.06145}, year={2017} }	Apostolos Pyrgelis, Carmela Troncoso, Emiliano de Cristofaro	Knock Knock, Who's There? Membership Inference on Aggregate Location Data	Membership inference attacks against location aggregates	Tabular	Linear-Queries	Membership-Inference	Empirical			Ana-Maria Cretu, EPFL Wes-Alexandre de Montjoye, Imperial College
https://arxiv.org/abs/2301.10053	(§Inproceedings/pinnamalia/2023)Inar, title=(A linear reconstruction approach for attribute inference attack against synthetic data), author=(Annamala), Meenatchi Sundaram Muthu Selva and Gadtut, Andrea and Rocher, Luc), bookttik=(Usenix Security), year=(2024)	Meenatchi Sundaram Muthu Selva Annamalai, Andrea Gadotti, Luc Rocher	A linear reconstruction approach for attribute inference attacks against synthetic data	Introduces a new attribute inference attack against synthetic data based on linear reconstruction methods for aggregate statistics, which target all records in the dataset, not only outliers.	Tabular	Generative - Model	Attribute inference	Empirical	https://github. com/synthetic- society/recon-synth		Georgi Ganev, UCL
https://www.orglodf/2206.10469, pdf	(garticle(carini)2022privacy, tibest-The privacy onion effect Memorization is authority-(Carlini, Nicholas and Jageldai, Mathwa and Sang, Chivan and Peprent, Nicolas and Terzis, Andreas and Traimer, Florian), journal-(Advances Inkural Metomation Processing System), System, (S), unare-(12332-13276), year-(1232)	Carlini et al.	The Privacy Onion Effect: Memorization is Relative	Removing vulnerable records makes other records vulnerable	Tabular	Predictive-Model	Membership-Inference	Empirical			Yves-Alexandre de Montjoye, Imperial College
https://brxiv.org/abs/2112.03570	(ii)inproceedings(zstrik)222/zmembership, title=l_Mometryik, interves attacks from first principles), authors (⁻ Gost, Berkholas and Chien, Stave and Naor, authors (⁻ Gost, Berkholas and Chien, Stave and Naor, authors (⁻ Gost, Berkholas), and Chien, Stave and Tramer, Florida, boottater (⁻ CO22 TEE Symposium on Security and Privacy (⁻ Sta), year-(12027), organization-(IEEE)	Carlini et al.	MembersNp Inference Attacks From First Principles	Takes a step back + new attack (LIRA)	Tabular	Predictive-Model	Membership-Inference	Theoretical			Yves-Alexandre de Montjoye, Imperial College
https://arxiv.org/abs/2003.14053	Berticklepsking/2020/meeting, titleel/meeting praciatist-bow cass by it to break privacy in forderized learning?), author=(Seiping, honas and Baueremister, Hartmut and Dr(Yoge, Hannah and Medler, Michael), journal=(Advances in enual information processing system), page=(1037-16947), year=(2020)	Geiping et al.	Inverting Gradients How easy is it to break privacy in federated learning?	Gradient inversion attack (reconstruct data point from gradient) - application to federated learning	Image	Predictive-Model	Reconstruction	Empirical	https://github. com/knastSelping/ breaching.		Aurélien Betlet, Inria
httos: Birchive dimacs.ntgers. edui-genhambutskaperskmold calerhuedt	Binproceedings(someak2013temprical, titlest-(Empirical mixes) and empirical, utility of anonymised data), author=(Cornoles, Graham and Pirocopiuc, Cacilia M and Shin, Emiropa and Shivatarao, Duxoh and Yu, booktter-(2013te E29th Instrutational Conference on Data Engineering Workshops (ICDEW)), page=(77-82), year-(2013), organization-(IEEE)	Cormode, G., Proceptur, C.M., Shen, E., Srivastava, D. and Yu, T	Empirical privacy and empirical utility of anonymized data.	Naive Bayes attacks against simple workloads of statistics	Tabular	Linear-Queries	Reconstruction	Empirical			James Honaker, Anonym
httos://projects.io.harvard. eduit/les/prixacytools/files/pdf_02 .edf	(Britiskipkovsk2017/exposed, tiskel-Epsposed as avery of attack on private data), author-(Poxork, Cynthia and Smith, Adam and Steinik journal-(Annual Review of Statistics and Its Applicats volume-14), number-[1], page=[01-94], yaa=-2017, publisher=(Annual Reviews)	Dwork, C., Smith, A., Steinke, T. and Ullman,	Exposed a survey of attacks on private	Survey of privacy attacks	Tabular			Theoretical			James Honaker, Anonym
https://encceedings.neurins. co/saper_files/saper/2023/file/9a 6f6e0dif/281d1cb866919240894 6d73-Paper-Conference.pdf	(a) article(steinka2024privacy, title=(Privacy auditing with one (1) training run), author=(Steinke, Thomas and Narr, Milad and Jagideki journal=(Advances in Neural Information Processing S volume=(36), year=(2024)	Steinke, T., Nasr, M. and Jagielski, M.	Privacy Auditing with One (1) Training Run.				Membership-Inference	Empirical			James Honaker, Anonym
https://ankvorg/adf/1610.05820. pdf	(in)proceedings(bheir/3017member/b), title-Uhenberkeip inference attack against machine is author-(Shokri, Reza and Stronati, Marco and Song, C booktite-(2017 IEEE symposium on security and priv gages-(3-18), year-(2017), organization-(IEEE))	Shokri, R., Stronati, M., Song, C. and Shmatil	Membership inference attacks against machine learning models.	The original membership inference based on shadow models			Membership-Inference	Empirical			James Honaker, Anonym
https://arxiv.org/abs/1512.0032Z	Ania.	Wagner, I. and Eckhoff, D.	survey.	Survey of privacy-loss metrics	Tabular	Linear-Queries	Information Leakage	Theoretical			James Honaker, Anonym
http://bitoumposium. endopets/2023boosts-2023- 0055.php	(generalized and the second se	Giami, M., Baenisch, F., Wehmeyer, C., and Tasnádi, B.	A Unified Framework for Quantifying Privacy Risk in Synthetic Data	Adversarial evoluation of singling out, Unlability, and inference risk in tabular synthetic data	Tabular			Empirical	https://jithub. com/statice/anony meter		Matteo Giomi, Anonos
https://arxiv.org/abs/2211.10459	· inproceedings/glomi/2022/unified, title-f_k unified framework for quantifying privacy risk nynthetic data], author-(cliomi, Matteo and Beenisch, Franziska and Whenheyer, Christoph and Tasn('a)di, Borb('a)la), bookttie-(PETs), year=(2023),)	Matteo Giomi, Franziska Boenisch, Christoph Wehmeyer, Borbála Tasnádi	A Unified Framework for Quantifying Privacy Risk in Synthetic Data	Present Anonymeter, a statistical framework to jointly quantity different types of privacy risks in synthetic tabular datasets. Equips this framework with attack-based ovaluations for the singling out, linkability, and inference risks, the three key indicators of factual anonymization according to the GDPR.	Tabular	Generative-Model	Membership-Inference	Empirical			Georgi Ganev, UCL

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Priviley Attacks Respository											
URL	BibTex (Please add a bibtex entry for this paper to facilitate writing our summary document)	Authors	Title	Short Description	Type of Data	Type of Release	Threat Model	Research Type	Links to Artifacts	Comments	Submitter (your name, affiliation)
https://anxiv.org/abs/2310.16789	(ijarticlejch2023detecting, title-(Detecting pertaining data from large language models), author-(SN, Weijia and Ajth, Anirudh and Xia, Mengshou and Huang, Yangubo and Liu, Daogao and Blevins, Terra and Chen, Dang ia and Zettlemoyer, Luke), journal-(arXiv preprint arXiv:2310.16789), year-(2023)	Weijia Shi et aL	Detecting Pretraining Data from Large Language Models	introduces Min-K prob attack: Membership Inforence attack against LLMs using average of lowest k probable tokens in the target sequence.	Text	Generative-Model	Membership-Inference	Applications	https://awi0419, github.io/detect- pretrain.github.io/		Hamid Mozaffari, Oracle Labs
	GimicsGause224eensberzeig, Hittel-(20 Menthering Inference Attacks: Work on Large Language Models), Hittel-(20 Menthering Inference Attacks: Work on Large Language Models), Hittel-(20 Menthering Inference Attacks: Work on Hittel-(20 Menthering), expert-164202.0741), archive/Hittel-(20 Menthering), expert-164202.0741), archive/Hittel-(20 Menthering), expert-164202.0741), archive/Hittel-(20 Menthering), expert-164202.0741), archive/Hittel-(20 Menthering), expert-164202.0741), archive/Hittel-(20 Menthering), expert-164202.0741), archive/Hittel-(20 Menthering), expert-164202.0741), archive/Hittel-(20 Menthering), expert-164202.0741), archive/Hittel-(20 Menthering), expert-164200.0741), archive/Hittel-(20 Menthering), expert-164000, Hittel-(20 Menthering), expert-164000, Hittel-(20 Menthering), expert-164000, Hittel-(20 Menthering), expert-164000, Hittel-(20 Menthering), expert-164000, Hittel-(20 Menthering), expert-164000, Hittel-(20 Menthering), expert-164000, Hittel-(20 Menthering), Hittel-(20	Method Duan Antoinnen Suri, Histoffe Metaloghalla Senen Me, Weija Sil, Lake Zettemoyer, Waii Twertko, Yain Choi, David Evans, Hannaneh Hajishirzi	Do Membership Inference Attucks	Examining MA attacks on LLM, proposing a giftub repo with set of standard stacks	Text	Generative-Model	Membership-Inference	Empirical	https://athub, com/amgroot42/mi mic		Danit Filerko, University of Washington
https://binkiorg/abs/2301.13188	Orticle(carlin)2023extracting. Utile=UticAttacting. trille=UticAttacting training data from diffusion models), autor=(Carlini, Kicholas and Hayes, Jamie and Naar, Milad and Japikiski, Matthew and Saltwag, Vilash and Trank(v), Frobana and Ballik, Bolya and Upobliko. Daphne and Wallace. Eric) jamat=(USENTS Sourby), vear=(2023) jamat=(LSENTS Sourby).	Nicholas Carlini, Jamie Hayes, Milad Nasr, Matthew Jaglelski, Vikash Schwag, Florian Tramèr, Borja Balle, Daphne Ippolito, Eric Wallace	Extracting training data from diffusion models	Show that diffusion models memorize individual images from their training data and emit them at generation time. With a generation and their pipeline, extracts over a thousand training examples from state-of-the-art models, ranging from photographs of individual people to trademarked company logos.	Image	Generative-Model	Data-Extraction	Empirical			Georgi Ganev, UCL
https://anxiv.org/abs/2012.07805	(ginproceedings;Gantu.22124xt2ctifg, tible=[Extercting training data from large language models), author=[Carlin, Nicholas and Tramer, Florian and Wallace, Eric and Jagleisk, Matthew and Herbert- Voss, Ariel and Leik, Katherine and Roberts, Adam and Brown, Tom and Song, Dawn and Erlingsson, Ulfar and others), year=(D221))	Nicolas Carlini, Florian Tramèr, Eric Wallace, Matthew Jagielski, Ariel Herbert- Voss, Katherine Lee, Adam Roberts, Tom Brown, Dawn Song, Uffar Friingsson, Alina Oprea, and Colin Raffel	Extracting training data from large language models.	Showed how to prompt models like GPT2 to reveal specific training examples	Text	Generative-Model	Data-Extraction	Applications			Jon Ullman, Northeastern University
https://anniv.org/pdf/2211.06550.pd	(Barticlefloussiau2022paps, title=[Tapas: toolbox for adversarial privacy auditing of synthetic data), author=[Houszia, Rovinnond and Jordon, James and Cohen, Samuel N and Dariot, Owen and Elilott, Andrew and Godes, James and Moke, Callum and Rangel-Smith, Camila and Szpruch, Lukasz], journal=[zxiV preprint arXiv:2211.06550], year=[2022]	Florimond Houssiau, James Jordon, Samuel N. Cohen, Owen Daniel, Andrew Elliott, James Gedder, Callum Mole, Camila Rangel-Smith, Lukazz Szpruch	Tapas: Toolbox for Adversarial Privacy Auditing of Synthetic Data	A system of classification of MIA attacks presented as part of a toolbox of attacks to evaluate synthetic data privacy under a wide range of scenarios	Tabular						Danili Filienko, University of Washington
https://brxiv.org/abs/1909.03935	(inproceedings(:hen2020gan, title+(Gan-lask: a taxonomy of membership inference attack: against openative models), author=(Chen, Dingfan and Yu, Ning and Zhang, Yang and Fitz, Margan ad Yu, Ning and Zhang, booktate=(ACM CCS),)	Dingfan Chen, Ning Yu, Yang Zhang, Mario Fritz	Gan-leaks: a taxonomy of membership inference attacks against generative models	Presents a taxionomy of membership inference attacks, encompassing not ones. Moreover, provides a thoevestically grounded attack calibration technique, which consistent yboots the attack performance in all cases, across different attack settings, data modalities, and training configurations.	Image	Generative-Model	Membership-Inference	Empirical			Georgi Ganev, UCL
https://arxiv.org/abs/1705.07663	(i)inproceedings/hayse2019/0gan, Utile=([LOGAN): membership inference attacks against generative models], author=(Hayse, Jamie and Mekis, Luca and Danezis, George and De Cristofano, Emiliano), booktite=(FPDFETs), year=(2019),	Jamie Hayes, Luca Melis, George Danezis, Emiliano De Cristofaro	LOGAN: Membership Inference Attacks Against Generative Models	Presents the first membership inference attack: against generative models (GANs): given a data point, the adversary determines whether or not it was used to train the model.	Image	Generative-Model	Membership-Inference	Empirical			Georgi Ganev, UCL
https://koskvorg/adl/2112.05307. adf	(Bipproceeding-Lipin222ve, titles-(Are verbrey 472 thing and floating-point attacks on differential privacy systems), author-[Ini, Jiakai and Mohrty, Eleanor and Rubinstan Benjamin IP and Dintmenko. Olga), boottiele (2022 Ele Symposium on Socurity and Proapet-472 - 488), var=(2022, organization=[EEE] }	Jin, McMurtry, Rubinstein, Ohrimenko	Are We There Yet? Timing and Floating-Point Attacks on Differential Privacy Systems	Attacks on DP implementations that use floating-point arithmetic; timing side channels on discrete samplers			Reconstruction	Applications			Zachary Ratliff, Harvard + OpenDP
https://brxiv.org/abs/2305.18462	(g)artick[enattern/2023membership, titlest_Membership) Interevos attacks against Language modés via neighbourhood comparison), author=(Nattern, Nattern and Schiff)(g)logof, Bernhard and Schin, Mirmiaya and Bernhard and Schiff Tarken), Mirmaya and Bernhard and Schiff (g)logof, Bernhard and Schiff, Niethand Andre Schiff, Schiff, Tarken), guarnal=(arXev preprint arXiv:2305.18462), year=(2023)	Justus Mattern et al.	Membership Inference Attacks against. Language Models via Neighbourhood Comparison	Memership inference attack agaisnt LLMs by generating neighbours which are perturbed text using a mask model Like BERT	Text	Generative-Model	Membership-Inference	Applications	https://github. com/m/reshghallah /neighborhood: curvature-mia		Hamid Mozaffari, Oracle Labs
https://anxiv.org/abs/2312.03262	(§inproceedings[parifade12024low, title=[Low-Cast High-Power Membership Inference Attacks], author=[Zartackh, Sajjad and Liu, Philippe and Shoki, Reza), bookthile=[Forty-first International Conference on Machine Learning], year=[2024])	Sajjad Zarifzadeh, Philippe Liu, Reza Shokri	Low-Cost High-Power Membership Inference Attacks	Efficient MIA with shadow models and auxiliary reference data. Outperfroms LIRA in cases where one has plenty of reference data and almost no reference models	Tabular	Predictive-Model	Membership-Inference	Empirical			Luca Melis, Meta
https://arxiv.org/abs/2302.12590	(Intricle/van2023membership, Utile_IMembership, inference attacks against synthetic data through overfitting detection), author=(van Bruegel, Boris and Sun, Hao and Qian, Zhaoshi and van der Schaar, Mhaela), journal=(AJRTATS), vea=[2023])	Boris van Breugel, Hao Sun, Zhaozhi Qian, Mihaela van der Schaar	Membership inference attacks against synthetic data through overfitting detection	Proposes DOMIAS, a density-based MIA model that aims to infer membership trageting local overfitting of the generative model assuming the attacker has some knowledge of the underlying data distribution.	Tabular	Generative - Model	Membership-Inference	Empirical			Georgi Ganev, UCL
https://aniv.org/abs/2111.09679	(iii)proceedings/ju2/22/anhanced, tills=(ii)Fancord minoscription (reference attacks) author=(ryb, Sinyuan and Maddi, Aadryaa and Maxinancha, Saik Kumar and Bindschandler, Vincent and Shoktke, Renza). booktate=(Proceedings of the 2022 ACM SIGSAC Conference Computer and Communications page=(-1009)- syam=(-2022) }	Jiayuan Ye, Aadyaa Maddi, Sari Kumar Murakonda, Vincent Bindischaedler, Reza Shokri	Enhanced Membership Inference Attacks against Machine Learning Models	Framework for MIA based on approximate LRT. Theory behind general class of attacks + a few instantiations.	Tabular	Predictive-Model	Membership-Inference	Empirical			
https://anvivorg/abs/2208.14933	(Einproceedings/III.2022/amembership, Utlan-Membership inference attack by exploiting loss author+(Liu, Ylyong and Zhao, Zhengyu and Backes, h booktitle-(Proceedings of the 2022 ACM SIGSAC Cor- pages=(2085-2098), year=(2022)	Yiyong Liu, Zhengyu Zhao, Michael Backes,	Membership inference attacks by exisiting loss trajectories	Membership inference attack based on knowledge distillation to form signals to attack via loss trajectories over multiple epochs.	Image	Predictive-Model	Membership-Inference	Empirical	https://github, com/DennisLiu202 2/Memberships Inference-Attacks, by-Exploiting, Loss-Trajectory		Johan Östman, Al Sweden
https://brok.org/abs/7307.03694	(guricie)pertran/024ccalable, tituels-Scalable memorphip inference attacks via quantite regression), author-gletran, Martin and Tang, Shuai and Roth, Auron and Kaarma, Michael and Morgenstern, Jamie H author-gletrand, Michael and Morgenstern, Jamie H Journal-(Advances in Neural Information Processing system/colored) vaar-(2024)	Martin Betram, Shuai Tang, Michael Kaarne, Jamie Morgenstern, Aaron Roth, Zhiwei Szeven Wu	Scalable Membership Inference Attacks via Quantile Regression	Membership inference attack that does not require shadow models but only to train a single regression model to predict quantiles of the logits.	Image	Predictive-Model	Membership-Inference	Empirical			Johan Östman, Al Sweden
https://aniv.org/abs/2007.14321	@inproceedings(chosenttac2011bbd), Utility(-bdd), only more attack), third-(bdd), only more attack), third-(bdd), only more attack), third-(bdd), and Paparok, Michael, booktice-(international conference on machine learning), page=(1964-1974), yaa=(2021), organization=(PMLR) } }	Christopher A. Choquette-Chox, Florian Tramer, Nicholas Carlini, Nicolas Papernot	Label-only membership inference attacks	Black-box membership inference attact with label-only access: Signals are created by probing the mode with permutations around a given datapoint.	Image	Predictive-Model	Membership-Inference	Empirical			Johan Östman, Al Sweden
https://openreview.net/pdf2 id=7WsbowyHrS	@inproceedings(wuyou, title=\fuo Only Query Once: An Efficient Label-Only Membership Internes Attack), author=\{Wu, Yutong and Qiu, Han and Guo, Shangwei and Li, Javei and Zhang, Tiarwei), booktite=\{The Weithh International Conference on Learning Representations)	Yutong Wu, Han Qiu, Shangwei Guo, Jiwei Li, Tianwei Zhang	You only query once: an efficient label- only membership inference attack	Strategies to craft query examples to reduce the required number of queries	Image	Predictive-Model	Membership-Inference	Empirical	https://aithub, com/WU-YU- TONG/YOQO		Johan Östman, Al Sweden

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	Dir Tau (Director add a billion anto da abile anno 44										
URL	Biblick (Pease add a biblex entry for this paper to facilitate writing our summary document)	Authors	Title	Short Description	Type of Data	Type of Release	Threat Model	Research Type	Links to Artifacts	Comments	Submitter (your name, affiliation)
https://openreview.net/forum2 id=fwztlgo0FM9y	(garnclaftpow.2021/0600m), ttile=(Robbing the fact: Directly obtaining private data in federated learning with modified models), author=(Fow). Liam and Geljong, Jonas and Czaja, Wojtek and Goldblum, Micah and Goldstein, Tom), journal=(atViv preprint arXiv:2110.13057), year=(2021)	L Fowl, J Geiping, W Czaja, M Goldblum, T Goldstein	Robbing the Fed: Directly Obtaining Private Data in Federated Learning with Modified Models	Malicious adversary to perform exact reconstruction of the training data in FL	Image	Predictive-Model	Reconstruction	Empirical	https://github. com/lonasGeiping/ breaching.		Dmitrii Usynin, TUM/imperial College London
https://anviv.org/abs/7201.12675	@articlefowl2022deceptions, title=[Deceptions: Compted transformers breach provery in federated learning for Language models], author=[FowL, Liam and Geiging, Jonas and Reich, Steven and Wine, Judia and Casju (Ngelk and Goldblum, Micah and Goldstein, Tom), journal=[JoNV prepint arXiv:2201.12675], year=[2022]	Llam Fowl, Jonas Geiping, Steven Reich, Yuxin Wen, Wogtek Czaja, Micah Goldblum, Tom Goldstein	Deceptions: Corrupted Transformers Breach Privacy in Federated Learning for Language Models	Model inversion attacks using a malicious attacker in transformer- based FL settings	Text	Predictive-Model	Reconstruction	Empirical	https://github. com/lonacGeiping/ breaching.		Dmitrii Usynin, TUM/Imperial College London
https://brviv.org/abs/2202.00580	(i]article/wen2022fiching, ttile=[Fiching for user data in large-batch federated learning via gradient magnification], author=(Wen, Yusin and Geiping, Jonas and Fowl, Liam and Goldstum, Micah and Goldstein, Tom), journal=[atViv preprint arXiv:2202.00580], year=(2022) }	Yuxin Wen, Jonas Gelping, Liam Fowl, Micah Goldblum, Tom Goldstein	Fishing for User Data in Large-Batch Federated Learning via Gradient Magnification	Malicious adversary to perform exact reconstruction of the training data in FL, this time with (almost) arbitrarily Large batch sizes	Image	Predictive-Model	Reconstruction	Empirical	httos://aithub, com/lonasGeiping/ breaching,		Dmitrii Usynin, TUM/mperial College London
https://acdu.org/abs/2112.02918	@inproceedings@borrich/02221urios. Utbel/When the utions abandon honexty: Federated learning in ext privatel, in ext privatel, interface and privately and Database and Database Honextree Networks and Database and Database Shumalan, lis and Papernet, Nicolas). boottise-(2022 IEEE Bit European Symposium on Security and Private (EuroDAP), privat-(2023, organization=(EEE))	Franziska Bosnisch, Adam Dziedzic, Roel Schuster, All Shahin Shamsabadi, Ilia Shumatov, Nicolas Papernot	When the Curious Abandon Honestry: Federated Learning Is Not Private	Mallidous FL input reconstruction using trap weights (model modification)	Image	Predictive-Model	Reconstruction	Empirical	https://bithub, com/lonas/Gelping/ breaching.		Dmitrii Uoynin, TUMimperial Cellege London
bttos:/koenaccess.thecvf, com/content/CVPER021.html/Via See Through Gradients Image. Batch: Recovery via Gradienversio n_CVPR_2021_esper.html	(iii)proceedings(i)(n2021se, title=[See through gradients: Image batch recovery via gradienersion), asthor-f/th. Hongou and Maliya, Arun and Vahdat, Arash and Analos, Jose M and Kaatz, Ian and Joseffang, Joseffang, Status, Joseffang, Status, Joseffang, Status, Joseffang, Status, Joseffang, Status, Joseffang, Joseff	Hongxu Yin, Anun Maliya, Arash Vahdat, Jose M. Aluarez, Jan Kautz, Pavlo Molchanov	See Through Gradients: Image Batch Recovery via Gradinversion	First demonstration of large batch-size model inversion in FL	Image	Predictive-Madel	Reconstruction	Empirical	<u>httos://github.</u> com/lonasGelping/ breaching.		Dmitrii Usynin, TUM/Imperial College London
httos-lisocossinos.mir. oros-k/2021/aritagos223a/kariyag gs23a.odf	(ii)inproceedings/Lauryapa20223acktal, Utel=(Cockta) arrya vtatc. Breaking aggregation- based privacy in federated learning using independent component analysis, and dose, Chaan and Maener, Kiwan and Kong, Weireja and Suk, Edeward and Qurenki, Mohraddin K and Lee, Heisen-Hein SJ, bootstalle-(hertomational Conference on Machine Learning), arryanization=(PMLR) ergenization=(PMLR)	Sanjay Kariyappa, Chuan Guo, Kiwan Maeng, Wenjia Xiong, G. Edward Suh, Moinuddin K. Quresh, Holen-Hein S. Lee	Coottail Party Attack Breaking Aggregation-Based Privacy in Federated Learning Using Independent Component Analysis	Theoretical attempts to present (and attack) secure aggregation in FL	Image	Predictive-Model	Reconstruction	Theoretical			Dmitrii Uoynin, TUMimperial Cellege London
htto://di.acm.org/tis/bbs/10. 1145/3597800	garticEstaynin0223bayood. tibel-(Bayood gardens: Exploitions ad dwersarial priors in model inversion attacks), autor-(Livym, Nomti and Rueckert, Daniel and autor-(Livym, Nomti and Rueckert, Daniel and parall-(ACM Transactions on Privacy and Security), number-(P), pages-(1-30), publisher-(ACM New York, NY)	Dmitril Usynin, Daniel Rueckert, Georgios Kalssis	Beyond Gradients: Exploiting Adversarial Priors in Model Inversion Attacks	More successful model inversion using HBC adversary with the knowledge of context and style of the training data	Image	Predictive-Model	Reconstruction	Empirical			Dmbril Usynin, TUM/Imperial College London
https://anxiv.org/abs/2404.02936	(Barticle/shang/2024min, Utto-plin-Ki+v- improved Baseline for Detecting Pro-Training Data from Large Language Models), author-(Zhang, Ingroga and Sku, Ill. Improvi and Yeats, Eric and Ouyang, Yang and Kuo, Martin and Zhang, Jannyi and Yang, Hao and Li, Haji, journal-(arXiv preprint arXiv:2404.02336), year-(2024)	Jingyang Zhang et al.	Min-K%++: Improved Baseline for Detecting Pre-Training Data from Large Language Models	Impvroved the Min-K attack by normalizing the log prob of tokens	Text	Generative-Model	Membership-Inference	Applications	https://wsteven. github.io/mink- plus-plus/		Hamid Mozaffari, Oracle Labs
https://petsymposium. org/2019/files/papers/issue4/bop ets-2019-0067.pdf	(i)inproceedings/hilprocht2013monte, title=([Monte carlo and reconstruction membership inference attack: against generative models]), author=(Hilprocht, Benjamin and H(*a)rterich, Martin and Bernau, Daniell, bootthte=(PoPETs), year=(2019), }	Benjamin Hilprecht, Martin Härterich, and Daniel Bernau	Monte Carlo and Reconstruction Membership Inference Attacks against Generative Models	Present two information leakage attacks that outperform previous work on membership inference against generative models.	Image	Generative - Model	Membership-Inference	Empirical			Georgi Ganev, UCL
https://arxiv.org/abs/2312.05114	() article(ganev/023insdequary, ttbie-[On the inadequary of Smlarity-based Physics Metrics: Resonance Smlarity-based Anonymous Synthetic Data"), Journal-[arXiv:2312.05114], Journal-[arXiv:2312.05114], }	Georgi Ganev, Emiliano De Cristofaro	On the Inadequacy of Similarity-based Privacy Metrics: Reconstruction Attacks against "Truly Anonymous Synthetic Data"	Reviews the privacy metrics offered by leading companies in this space and sheds light on a few critical flaws: In reasoning about privacy entried via empirical evaluations. Presents a reconstruction attack, ReconSyn, which successfully recovers at least 72% of the low-density train records [or outlier] with only black-box access to a single fitted generative model and the privacy metrics.	Tabular	Generative-Model	Reconstruction	Empirical			Georgi Ganev, UCL
https://arxiv.org/abs/2102.03314	(i)inproceedings(pprisanu/2022on, title=(On utility and privacy in synthetic genomic data), author=(Oprisanu, Britstena and Ganev, Georgi and De Cristofaro, Emiliano), booktitle=(PNDSS), yaar=(2022) }	Bristena Oprisanu, Georgi Ganev, Emiliano De Cristofaro	On utility and privacy in synthetic genomic data	Provides the first evaluation of both utility and privacy protection of six state-of-the-art models for generating synthetic genomic data. The experiments show that no single approach to generate synthetic genomic data yields both high utility and strong privacy across the board.	Tabular	Generative-Model	Membership-Inference	Empirical			Georgi Ganev, UCL
https://aniv.org/adi/2302.03098. adf	(Barticlandrew 2023one, Utile-(Dio-et-orpical privacy estimation for foderated learning), author-(Endree, Galen and Kalvacz, Peter and Oh, Seevoong and Oprea, Alina and McMahan, H Brendan and Suryakamar, Vinith), journal-(a/bV ope)nt arXiv:2302.03098), year=(2023)	Galen Andrew, Peter Kairouz, Sewoong Oh, Alina Oprea, H. Brendan McMahan, Vinith M. Suriyakumar	One-shot Empirical Privacy Estimation for Federated Learning	Presents an apporach for performing a strong white-box attack for measuring the DP epsilon of ML training algos in 1 training run.		Generative-Model	Membership-Inference				Peter Kairouz, Google
https://seesring.ice.org/dourne	@INPROCEEDINCS[J822311, auto-ref"tons. Small and cashin bookstie-(2018 IEEE 31s. Compared Security Foundations: Symposium (SF)). Utile-(Phocay Risk in Machine Learning Analyzing Utile-(Phocay Risk in Machine Learning Analyzing Variane-). auto-pho- analysis. J Jack Strategy (Strategy), Jack Strategy, Jack Variane-). Instance of the Strategy (Strategy), Jack Strategy, Jack Variane-). Instance of the Strategy (Strategy), Jack Strategy, Jack Variane-). Instance of the Strategy (Strategy), Jack Strategy, Jack Variane-).	Samuti Yoon; Irone Giaconelli; Matt Predriksor; Somesh Jha	Privacy Bick in Machine Learning: Analyzing the Connection to Overfitting	MIA attack based on final loss for LLMs	Text	Generative-Model	Membership-Inference	Empirical			Danië Fëlerko, University of Washington
https://anxiv.org/abs/2203.03929	[Barticle/inveshpatalah2022quantifying, title=(Quantifying privary risks of masked language models using membership inference attacks), author-(Mireshpatalah. Tatemehrsadar and Goyal, Kartis and Urivay, Archis and Berg-Nispatrick. Taylor and Shokri, Roza), Journal=[J2002 proprint arXiv:2203.03929], ysa=r02022] J	Fatemehsadat Mineshghallah, Kartik Goyal, Archit Uniyal, Taylor Berg-Kirkpatrick, Reza Shekri	Quantifying Privacy Risks of Masked Language Models Using Membership Inference Attacks	Membership inference attack based on likelihood ratio hypothesis testing that involves an additional reference MLM to more accurately quantify the privacy risks of memorization in MLMs.	Text	Generative-Model	Membership-Inference	Applications			Daniil Filienko, University of Washington
https://www.bu/231117035	(garticle/par2023.cctable. title-Sctable carction of training data from (groduction) language models). author-Nivar, Niva Ali and Carlini, Norbais and Hayase, Isonithan and Jagidiski, Matthew and Cooper. A Folger and Igoolatik Daylow and Cooper. A Folger and Igoolatik. Daylow and Cooper. Proiran and Lee, Katherine). year=(2023) year=(2023)	Milad Nasr, Nicholas Carlini, Jonsthan Hayasa, Matthow Jageiski, A. Feder Cooper, Daphne Ipoolito, Christopher A. Onoquetto-Choo, Eric Wallaco, Florian Trambr, Katherine Lee	Scalable extraction of training data from (production) language models	Studies extractable memoritation: training diata that an adversary can efficiently extract by querying a machine learning model without prior knowledge of the training dataset. Shows an adversary can extract gigabytes of training data from open- source language models like Pythia LlaMa or Faicon, and closed models like ChatGPT.	Text	Generative-Model	Data-Extraction	Empirical			Georgi Ganev, UCL
https://antivorg/abs/2101.04535	(E)Inproceedings/bas2022134/werany, titles/Adversary, instantiation tower bounds for differentially private machine learning), author=Niex, Millia and Song, Shaung and Thakurta, Abinatosep and Papernet, Nicolas and Cartin, Nicholas), booktitis=(IEEE S\&P), year=(2021) }	Milad Nasr, Shuang Song, Abhradeep Thakurta, Nicolas Papernot, Nicholas Carlini	Adversary instantiation: lower bounds for differentially private machine learning	Instantiates a hypothetical adversary in order to establish lower bounds on the probability that the distinguishing game can be won. Uses this adversary to evaluate the importance of the adversary capabilities allowed in the privacy analysis of DP training algorithms.	Image	Predictive-Model	Membership-Inference	Empirical			Georgi Ganev, UCL

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Privacy Attacks Respository											
URL	BibTex (Please add a bibtex entry for this paper to	Authors	Title	Short Description	Type of Data	Type of Release	Threat Model	Research Type	Links to Artifacts	Comments	Submitter (your name, affiliation)
https://arxiv.org/abs/2403.06634	Justice wrong our autory socialities, Guride (arkin)/2024 statuling, title=[Sealing part of a production language model], autoric=[Carlin, Nichanamurhy ()) and Sainka. Thomas autoric=[Carlin, Nichanamurhy ()) and Sainka. Thomas Listenica and patient and Sainka. Thomas Listenica and Sainka. Thomas Listenica and Sainka. Thomas Listenica and Sainka. Thomas Listenica and Listenica and Sainka. Thomas Listenica and Listenica and Sainka. Thomas Listenica and Listenica a	Nicholas Carlini, Danieł Pałoka, Krishnamurthy (DJ) Dvijotham. Thomas Steinke, Jonathan Hayase, A. Feder Coper, Katherine Lee, Matthew Jagielski, Milad Nasr, Arthur Commy, Eric Wallace, David Rolnick, Florian Tramèr	Stealing Part of a Production Language Model	Recovers the embedding projection layer (up to symmetries) of a transformer model, given typical black- box (API) access	Text	Generative-Model	Data-Extraction	Applications			Danill Fölenko, University of Washington
https:/brxiv.org/adf/2011.07018. pdf	Glipproceedings(Estable 2022s)withetic: Utlan=[Synthetic dataanonymisation groundhog day], author=(Stater, Thereia and Oprisanu, Bristena and Troncoco, Carmela), booktitel=[31 st USENX Security Symposium (USENIX Security 22), page=[1451-1468], yea=[2022]]	Stadler et al.	Synthetic Data - Anonymisation Groundhog Day	Black-box attack on synthetic data and quantitative evaluation of privacy of synthetic data	Tabular	Generative-Model	Membership-Inference	Empirical			Wes-Alexandre de Montjoye, Imperial College
https://knviv.org/abs/7302.07956	(inproceedings/has2022tight, title=\Tght Auditog of Differentially Private Machine Lances, Lances, Sainaka and Janie Hayes and Thomas Sainaka and Borjs Balla and Fortion. Tram() of rad Matthew Jagistiki and Nicholas Carlini and Andrase Terrish, boottite=(USENK Society), year = (2023)	Milad Nasr, Jamie Hayes, Thomas Steinke, Borja Balle, Florian Tramèr, Matthew Jagietski, Nicholas Carlini, Andreas Terzis	Tight Auditing of Differentially Private Machine Learning	Designs an improved auditing scheme that yields tight privacy settimates for natural (not adversarially crated) datasets if the adversary can see all model updates during training. Moreover, the auditing scheme requires only two training runs (instead of thousands) to produce tight privacy estimates, by adapting recent advances in tight composition theorems for differential privacy.	Image	Predictive-Model	Membership-Inference	Empirical			Georgi Ganev, UCL
bttos:/bl.acm.org/sb/10. 1145/3291276.3295691	() article/garfinks/2019understanding, title-{Understanding database reconstruction anamor-(Sarfinks). Smoon and Abovd, John M and Martinadae, (Dmitsing), journal-(ACM Quoud), yaar2019), }	Simson Garfiniel, John M Abowd, Christian Martindale	Understanding database reconstruction attacks on public data	Database reconstruction starks can be performed by using publiched statistical tables to create a set of mathematical constraints and then solving the resulting set of simultaneous capations. Shows how such an attack can be addressed by adding noise to the publiched tablations, so that the reconstruction to longer results in the original data. This has implications for the 2020 Census.	Tabular	Linear-Queries	Reconstruction	Empirical			Georgi Ganev, UCL
https://kinviv.org/abs/2307.01701	(ii)article(giupe)n2023/yrthetic, title=[Synthetic is all you need removing the auxiliary data assumption for membership inference attacks against cynthetic data], author=[Gur(Vg)pin, Florent and Mouse, Matthieu and Cretu, Ana-Maria and de Montjove, Yves-Alexandre], journal=[GaVC320.01201], year=[C023] }	Florent Guépin, Matthieu Meeus, Ana- Maria Cretu, Yves-Alexandre de Montjoye	Synthetic is all you need: removing the auxiliary data assumption for membership inference attacks against synthetic data	Develops new MIAs performed using only the synthetic data in three different sconarios: [51] Black-box access to the generator, [52] only access to the released synthetic dataset and [53] a theoretical setup as upper bound for the attack performance.	Tabular	Generative-Model	Membership-Inference	Empirical			Georgi Ganev, UCL
https://boxiv.org/abs/2206.07758	@inproceedings(haim2022reconstructing, title=[Reconstructing training data from trained neural network], Nv and Vardi, Gal and Yehudai, Gilad and Irani, Midha and Shamir, Ohad), booktitle=[NeurIPS], year=[2022], }	Niv Haim, Gal Vardi, Gilad Yehudai, Ohad Shamir, Michal Irani	Reconstructing Training Data from Trained Neural Networks	Shows that in some cases a significant fraction of the training data can in fact be reconstructed from the parameters of a trained neural network classifier. Propose a novel reconstruction scheme that stems from recent theoretical results about the implicit bias in training neural networks with gradient-biased methods.	Image	Predictive-Model	Reconstruction	Empirical	https://ailadude1, github, io/reconstruction/		Georgi Ganev, UCL
https://arxiv.org/abs/2201.04845	@inproceedings/balle2022reconstructing, title=(Reconstructing training data with informed adversarie), author=(Falle, Borja and Cherubin, Giovanni and Hayes, Jamie), booktrule=(EEE SV&P), year=(2022), }	Borja Balle, Giovanni Cherubin, Jamie Hayes	Reconstructing training data with informed adversaries	Studies how given access to a machine learning model an adversary can reconstruct the model's training data from the lens of a powerful informed adversary who knows all the training data points except one.	Image	Predictive-Model	Reconstruction	Empirical			Georgi Ganev, UCL
https://www.usenix. org/outer/Missher20summer_s alem_prepub.pdf	©inproceedings(Falem2020/bupdates, title=(Updates-leak: Data set inference and reconstruction attacks in online learning), author=(Salem, Ahmed Mohamed Gamal and Bhattacharyya, Aprolim and Backes, Michael and Fritz, Mario and Zhang, Yang), booktitle=(UESKV Security), year=(2020), }	Ahmed Salem, Apratim Bhattacharya, Michael Backes, Mario Fritz, Yang Zhang	Updates-leak: Data set inference and reconstruction attacks in online learning	Investigate whether the change in the output of a black-box ML model before and after being updated can leak information of the dataset used to perform the update, namely the updating set. Proposes four attacks following an encoder-decoder formulation, which allows informing diverse information of the updating set.	Image	Predictive-Model	Reconstruction	Empirical			Georgi Ganev, UCL
https://dl.acm.org/doi/pdf/10. 1145/3576915.3616602	@inproceedings[lokna2023group, ttile=[Group and Attack.Auditing Differential Privacy], author=[Lokna.Johan and Paradik, Anouk and Dimitrov, Dimitra and Vachev, Martin], booktile=[CCS], year=[2023]	Johan Lokna, Anouk Paradis, Dimitar I. Dimitrov, Martin Vachev	Group and Attack: Auditing Differential Privacy	Present a novel method to efficiently discover (r, d) differential privacy violations based on the key insight that many (r, d) pairs can be grouped as they result in the same algorithm. Crucially, the method is orthogonal to existing approaches and, when combined, results in a faster and more precise violation search.			Information Leakage	Empirical	https://github. com/eth-sri/Delta, Siege		Georgi Ganev, UCL
https://knviv.org/abs/1802.08232	(Inproceedings(zarlin)2019keret, title=The serect share: Evaluating and testing unintended memorization in neural networks), suther=(Zarlin, Kholas and Lu, Chang and Erlingscon, (VL)far and Kos, kernej and Song, Dawn), booktistle=(ZBN USENX security symposium (USENX security 19), page=(ZE7-284), var=(2019)	Nicholas Carlini, Chang Liu, Útfar Ertingsson, Jernej Kos, Dawn Song	The Secret Sharer: Evaluating and Testing Unintended Memorization in Neural Networks	Describes a testing methodology for quantitatively assessing the risk that rare or unique training-data sequences are unintentionally memorized by generative sequence models.	Text	Generative-Model	Data+Extraction	Empirical			Georgi Ganev, UCL
https://kinviv.org/abs/7202.12219	Intricle(tramer2022debugging, ttie=(Debugging Differential Privacy: A Case Study for Privacy: Auditing), author=(Tramer, Florian and Terzis, Andreas and Stelnke, Thomas and Song, Shuang and Jagidski, Matthew and Cartini, Nicholas), journal=(arXiv:22).122(19), year=(2022)	Florian Tramer, Andreas Terzis, Thomas Steirkis, Shuang Song, Matthew Jagielski, Nicholas Carlini	Debugging Differential Privacy: A Case Study for Privacy Auditing	Inspired by recent advances in auditing which have been used for estimating lower bounds on differentially private algorithms, shows that auditing can also be used to find flaws in (purportedly) differentially private schemes.	Image	Predictive-Model	Information Leakage	Empirical			Georgi Ganev, UCL
https://kirxiv.org/ahs/2206.05199	elipsproceding/caratelia2023bayesian, Ether-Bayesian estimation of differential privacy), author-(Zanelia-B(V)ejpaulic, Santiaga and Wutchitt, Licka and Polys, Shuti and Salem, Ahmed and R(V)lyle, Victor and Powerd, Andrew and Naset, Mohammad and K(Vojef, Boris and Jones, Daniel), bootstita-(CAL), yaa-(2023)	Santiago Zanella-Béguelin, Lukas Wutschitz, Shruti Tople, Ahmed Salem, Victor Rühle, Andrew Paverd, Mohammad Naseri, Boris Kögf, Daniel Jones	Bayesian Estimation of Differential Privacy	Proposes a novel Bayesian method that greatly reduces sample size, and adapt and validate a heuristic to draw more than one sample per trained model. The Bayesian method exploits the hypothesic starting interpretation of differential privacy to obtain a posterior for e (not just a confidence interval) from the joint posterior of the false positive and false negative rates of membership informeron attacks.	Image	Predictive-Model	Information Leakage	Empirical			Georgi Ganev, UCL
https://files.sri.inf.ethz. chiwebsite/papers/sp21- dosnicer.pdf	(i)Inproceedings(biches/2021dp, ttle=(De-Seiper Elack-Box Discovery of Differential Proacy Violations using Classifiers), author=(Bichsel, Benjamin and Steffen, Samuel and Bogunoix, III, and Vechev, Martin), booktite=(IEEE Si&P), year=(2021) }	Benjamin Bichsel, Samuel Steffen, Ilija Bogunovic, Martin Vechev	DP-Sniper: Black-Box Discovery of Differential Privacy Violations using Classifier	Present DP-Sniper, a practical black- box method that automatically finds violations of differential privacy.	Tabular		Information Leakage	Empirical			Georgi Ganev, UCL
bttps://anix.org/bdf/2310.09266. pdf	(Barticle/Bandp312023usr, title-User interese attacks on large language models), author-(Kradpal, Nikhil and Pillutla, Krishna and Oprea, Alina and Kairouz, Peter and Choquette-Choo, Christopher A and Xu, Zheng), Journal-(arXiv preprint arXiv:2310.09266), year-(2023)	Nikhi Kandgal, Krishna Pillutla, Alina Oprea, Peter Kairour, Christopher A. Choquette-Choo, Zheng Xu	User Inference Attacks on Large Language Models	Presents an attack for inferencing the precensplabsence of a user in the fine- tuning set of an LLM. The adversary is not assumed to know all the fine- tuning examples of a user only a subset (including some examples that weren't used even if the user participated in the fine-tuning stage).		Generative-Model	Membership-Inference	Empirical			Peter Kairouz, Google
https://brxiv.org/abs/7406.11544	(i)inproceedings(pur2024do, tti = (DD Parameters Reveal More than Loss for Memberchip Inference?), suthor = (Anthuman Suri and Xiao Zhang and David Evang), booktitle = (Morkshop on High-dimensional Learning Dynamics (HLD) (LCML), your = (2024, url = (intps:/janak.org/abs/2406.11544))	Anshuman Suri, Xiao Zhang, David Evans	Do Parameters Reveal More than Loss for Membership Inference?	The paper shows how prior claims about black-box access sufficing for optimal membership inference do not hold for most useful settings such as SGD	Tabular	Predictive-Model	Membership-Inference	Theoretical	https://github. com/amgroot42/lh a_hild		Anshuman Suri, UVA
https://krxiv.org/khs/2402.10001	, (IINPROCEEDINGS(EIMrin22024a, author = ([E] Min0), Abdellah and (Cyffers), Edwige and (Bollet), Autr(%)[en], tilla = ([P/rivacy (Alttacks in [D]) centralizad (L]earning), booktitle = ([ICML]), year = (2024))	Abdellah El Mrini, Edwige Cyffers, Aurélien E	Privacy Attacks in Decentralized Learning	The paper designs data reconstruction attacks against Decentralized SGD (where nodes in a communication graph alternate between local gradient steps and averaging steps with their engibbors. They show it is possible for a small subset of (honest but curious) attacker nodes to reconstruct the data from even distant nodes in the graph.	Image	Predictive-Model	Reconstruction	Empirical	https://github. com/AbdellahElmri ni/decAttack		Aurdöen Bellet, Inria

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Privacy Attacks Respository											
URL	BibTex (Please add a bibtex entry for this paper to	Authors	Title	Short Description	Type of Data	Type of Release	Threat Model	Research Type	Links to Artifacts	Comments	Submitter (your name, affiliation)
https://www.coglabs/2105.03408	Tabilitati withing our summary document) (Genocontent) (miles ADU Tabiothi, Miles and Prasask Tarihti and Shoko, igar and Timere, Reina's Document of the Shoko, igar and Timere, Tabiothi, and Document of the Shoko, igar and Timere, Tabiothi, and Document of the Shoko, and Timere, Tabiothi, and Document of the Shoko, and Timere, Tabiothi, and Timere, Tabiothi, and Timere, Tabiothi, and Timere, Tabiothi, and Timere, Tabiothi, and Timere, Tabiothi, and Timere, Ti	Mani Malek, Bya Mitonov, Karthik Possal, Igar Shalov, Florian Tramër	Antipodes of Label Differential Privacy. PATE and ALIBI	Label-inference attack against two LabelDP mechanisms for image classification	Image	Predictive-Model	Attribute inference	Empirical	https://github. com/facebooknessa rph/label.do.antio adsorbeenmaintee morization_attack		llya Mironov, Meta
bites:first-orghet/2212.10986	ginePeoCEDIMGs (pate-2023-ek, autor (A. Salem and C. Chenkin and D. Evens and B. Gogt and A. Paveral and A. Saru and S. Topia and S. Darasa (Bageard), <i>Constant Begard</i>), <i>Constant Begard</i> , <i>Names</i> (Ed. Ph), the [SSR2] (path the Privacy Games Beger (A) Linder Transmitter of Data Inference Privacy in year = (2023), pages = (2023-2345), doi:10.1016/948-0223.2023.2027.9213) doi:10.1016/948-023.2023.2027.9213, doi:10.1016/948-024.2023.2023.2027.9213, doi:10.1016/948-024.2023.2023.2027.9213, doi:10.1016/948-024.2023.2023.2027.9213, doi:10.1016/948-024.2023.2023.2027.9213, doi:10.1016/948-024.2023.2023.2027.9213, doi:10.1016/948-024.2023.2023.2027.9213, doi:10.1016/948-024.2023.2023.2027.9213, doi:10.1016/948-024.2023.2023.2023.2027.9213, doi:10.1016/948-024.2023.2023.2023.2027.9213, doi:10.1016/948-024.2023.2023.2027.9213, doi:10.1016/948-024.2023.2023.2027.9213, doi:10.1016/948-024.2023.2023.2027.9213, doi:10.1016/948-024.2023.2023.2027.9213, doi:10.1016/948-024.2023.2023.2023.2023.2023.2023.2023.2	Ahmad Salam, Ginoomi Chandah, David Grans, Bircis Kogd, Andrean Parent, Anchuman Satu, Yakuru Tople, Santiago Zanella-Béguatin	Sol: Let the Privacy Games Begin! A Unified Treatment of Data Inference Privacy in Machine Learning	Systematization of Knowledge of data Inference attacks using a privacy-game framework.				Theoretical			llya Mironov, Meta
https://www.bas/2111.08440	(iiipproceeding)entoxi022-diffuction, iiipproceeding) (iiipproceeding) (iiipproceeding) (iiipproceeding) (iiipproceeding) (iiipproceeding) (iiipproceeding) (iiipproceeding) (iiipproceeding) (iipproceeding) (iipproceed	Lauren Watson, Chuan Guo, Graham Cormode, Alex Sablayrolles	On the Importance of Difficulty Calibration in Membership Inference Attacks	Improvement in membership inference attacks by taking into account the difficulty of correct classification	Image, tabular	Predictive-Model	Membership-Inference	Empirical	https://github. com/facebookressa uchkalibration.me mbership		liya Mironov, Meta
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httes-Östxivorgöbs/1807.09173	@ARTICLE[Fueux2021, author=[thos: Skerp and Liu, Ling and Gursoy, Mehmet time and Yu, Lei and Wu, Weng), journal=IEEE Transactions on Service Compating), titles-[Demystäving Membership Interence Attacks in Machine Learning as a Service], year=(2021), mamber=[6], pages=(2073-2089), doi=[0.1109775C2019.29.29554))	Stacey Tuex, Ling Liu, Mehmet Emre Gursey, Lei Yu, and Wenqi Wei	Demystifying Membership Inference Attacks in Machine Learning as a Service	 MIA in the style of Shokri et al. '17 with shadow models with architecture different from that of the target model. MA with access to training gradients in the federated setting. 	Image, tabular	Predictive-Model	Membership-Inference	Empirical			Ilya Mironov, Meta
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