experiments：

我们的训练过程：

discovery strategy

covery To utilize unlabeled data, we propose a simple trigger-based latent instance discovery strategy, which can automatically label trigger words and event types for raw data. The trigger-based strategy is based on a heuristic assumption that if a given word serves as the trigger in a known instance, all other instances mentioning this word in raw data are latent instances and may also express an event. For example, the word “married” serves as the trigger in the instance “Mark Twain and Olivia Langdon married in 1870” to expose the event “Marry”, and then all instances in unlabeled data containing the word “married” will be picked up and added into a latent instance candidate set. As compared with the sophi 1003 rules used in existing weakly supervised ED models, our trigger-based latent instance discovery is simple, without the need of considering the correlation among words, triggers, and event types. Because our strategy is less restrictive, it is effective and efficient to obtain a large-scale candidate set without any special manual design. Meanwhile, the candidate set can cover much more instances and topics than the existing strategies.

先用supervised训练encoder和d，

When adapting our adversarial training strategy for semi-supervised scenarios, we first use the small-scale labeled data to pretrain the encoder and discriminator to let them gain the ability to detect event triggers and identify event types to a certain extent. Then, we construct a large-scale latent candidate set based on our instance discovery strategy with the trigger words in the labeled data as heuristic seeds. We use the pretrained encoder and discriminator to automatically label triggers and event types for all instances in the candidate set to build noisy large-scale data. With the small-scale labeled data as the reliable set R and the large-scale auto-labeled data as the unreliable set U, we can optimize the encoder, discriminator, and generator together to carry out adversarial training. During the adversarial training, when the discriminator and generator reach a balance after certain training epochs, all instances from the unreliable set U recommended by the generator and regarded as being labeled correctly by the discriminator will be adjusted from U to R. Conducting adversarial training iteratively can identify informative instances and filter out noisy instances in U, and accomplish utilizing large-scale unlabeled data to enrich small-scale labeled data.

8 KBGAN：

KG通常包含的是正样本，利用负样本情况较少。将头实体或者尾实体换成随机选择的实体是传统方法生成负样本，这种负样本迷惑性不好，提升也不大。本文用KG embedding model作为负样本生成器，来对抗训练分类器。

例如：xxx位于某座城市，将尾实体随机替换，得到的负样本大概率是错误的，不具有迷惑性。

架构：

G对负样本算一个概率，然后选择一个作为输出。使得负样本

D 降低G输出的负样本和相应的正样本 的margin loss by梯度下降

训练：

预训练D和G

对抗训练得到D

48：Incorporating gan for negative sampling in knowledge representation learning.

使用GAN生成负样本，提升知识表示学习。

作者认为传统表示学习在学习embedding过程需要利用负样本一起构造margin-based ranking损失函数，而以往的工作都是通过随机的方式构造负样本，这样的样本会影响模型的学习效果，于是本文提出一种基于对抗学习（GAN）的框架获取高质量的负样本，用GAN中的判别器学习KG中实体和关系的表示。本文的主要思路是合并基于GAN的框架到传统的方法提升表示学习的能力，实验证明这种融入在三元组分类和链接预测上的结果优于baseline模型。

作者把常规模型的通过训练最小化margin-based ranking loss作为判别器，把学习得到高质量负样本避免判别器出现zero loss作为生成器，通过判别器学到的embeddings作为KG的最终表示。论文的贡献是通过合并基于GAN的训练框架，让生成器产生高质量负样本，加强了baseline表示学习模型的能力。

生成器：

判别器：

实验部分：

未来工作：

框架泛化到其他问题的负样本生成，生成器采用复杂的模型。