Response to Reviewer 2 Comments

The authors of “Conditional Generative Adversarial Networks for Domain Transfer: A Survey” perform a comprehensive survey of the use of conditional GANs in the field of domain adaptation. The abstract is accurate. Major pluses of the introduction section are that it is relevant and cites the most important literature.
However, there are important aspects of the paper that are missing for it to be considered a survey.

1. The study needs to disclose the bibliographic method, - since those are not given it is not possible to reason whether the tools used for the completion of the study are suitable and correct

Response: Thanks for your comments very much. This paper is a research review to summarize and discuss the existing studies in the field of CGAN, to make people easily understand CGAN. Therefore, the bibliographic method is manual search and selection of appropriate literatures.

2. The study needs to disclose the inclusion criteria for the referenced papers

Response: Thanks for your comments very much. The reference includes some published papers by SCI journals or conferences, widely recognized papers (or highly cited papers) in this field, and a few novel papers. And we have added the explanation in the introduction with red fonts.

3. Since a survey needs to be especially aware of the research landscape the study needs to relate itself to the surveys that are already published in the topic of GANs in transfer learning / domain adaptation -> define clearly in the introduction section how is it different and what makes it unique

Response: Thanks for your comments very much. There are many surveys on GANs, but few of them concentrated on the topic of CGANs in transfer learning. Therefore, this paper aims to conduct a comprehensive survey on the research of CGANs. This paper mainly focuses on the development and application of CGAN. Finally, we also discuss the problems and challenges of CGANs, encouraging more researchers to study CGAN and apply it into more application fields. We have concluded these in the introduction with red fonts.

4. A standard practice for survey papers is to briefly delineate the research in numbers - how many papers were inspected, how many were identified to fit the criteria, how many are included in the study

Response: Thanks for your comments very much. We have manually inspected almost 190 papers about CGANs, while some of them are not officially published or have similar ideas. Therefore, the final listed references are carefully selected by us.

5. The inclusion of sections 2 and 3 is welcome and makes the paper more valuable to readers from outside the immediate field. For better ogranisation, both those sections and all their

children should be subsectioned under an encompassing ‘Methods’ section.

Response: Thanks for your comments very much. We have combined them into one section 2: The development methods of CGAN.

6. It is not clear how the ‘semantic level’ was assigned in Table 4. While there is a description provided in lines 367-370, it is not supported by any reference, nor experimental results. It is also confusing as to why coloring in a line drawing would be at a different semantic level than converting sketch to a photo.

Response: Thanks for your comments very much. In fact, line coloring is only a change in color pixels of an image, while converting a sketch into a photo involves a change in the overall style of the image, it is a change in the higher semantic level of the image. There is a big difference in the style of different paintings, such as realistic style, ink style, dark style, etc. Therefore, the style change involves more than just color change. The semantic levels of an image can also be divided as visual layer (low level), object layer (middle level) and concept layer (high level). The low-level semantics is the color, shape, texture and so on of an image; the middle-level includes the attributes and features of the image, which is the state of a partial object at a certain moment in the image; the concept layer is the high-level, which is the overall content shown by images to humans. We have revised the explanation with red fonts.

7. The manuscripts contains comments like “ Intuitively speaking, if CGAN is compared to the human brain, a person who has never been to the city but has seen countless rural sunrises and sunsets can hardly imagine what the urban evening looks like.”, which are not supported by any kind of research, and could simply be not true - in this particular case humans can easily imagine all sorts of sceneries which never existed - just look at concept art to any sci-fi intellectual property. Comments which are not supported by an adequate reference or by experimental results are a case of commenting beyond the scope of the article, and should be eliminated from a scientific paper.

Response: Thanks for your comments very much. We have checked and revised it.

8. The paper does not provide any closing discussion, and the conclusion section is merely an abbreviated abstract. The remaining problem and challenges section however is a big plus.

Response: Thanks for your comments very much. We have added some closing conclusions in Section 6 with red fonts, i.e., “This paper focuses on the research of CGAN in domain transfer, and introduces the development process of CGAN from the perspectives of: the principle of CGAN, the development of loss function, the model variants of CGAN, evaluation methods and application fields. These studies fully demonstrate that the CGAN model has great potential and research value.” “However, due to the short life of CGAN to date, it is still in the initial stage of development, and the relevant theories and applications are far from maturity yet. Meanwhile, we have also discussed and listed the future development directions of CGAN in Section 5. In summary, more investigations on CGAN are necessary for consolidating its development and we hope this paper will contribute

to researchers interested in applying CGAN in different domains.". The remaining problem and challenges section is our discussions and the possible future directions on CGAN. We have also modified some redundant parts, as follows:

5. The remaining problems and challenges

Although CGAN has made great progress in recent years, compared with many other sub-fields of artificial intelligence, it still faces many problems and challenges. Here are a few insights gained from our literature review.

- **Conditions are ignored.** ~~Compared with unconditional GAN, the biggest advantage of CGAN is that the same model can generate data with different characteristics after receiving the conditions.~~ [A1] Many CGAN models are easy to ignore the conditions and generate data failing to meet the conditions in some practical applications. Currently there are maybe [A1] two causes for this problem. First, the characteristics of samples under different conditions in the training set are not significantly different, that is, the model cannot accurately classify samples according to conditions. Second, the network architecture is not reasonable. For example, the conditions representing high-level semantics of data only act on the first half of the network, resulting in only affecting low-level semantics of data. ~~However, the above reasons are only the experiences explored by the past researchers in the actual model, and have not been strictly proved theoretically.~~ [A1]
- **Proper coding of conditions.** In order to make the CGAN model easy to be trained, conditions need to be coded. ~~For instance, Convolution Neural Network (CNN) is a common operation for extracting the main feature of images. However, if CNN is used to process the image, the derived code may no longer contain the details that essentially correspond to the characteristics of the generated image. Similar problems appear when the condition is other binary data.~~ [A1] However, how to have the reasonable encoding of conditions is a problem that needs further study in the field of CGAN. Because the common used Convolution Neural Network (CNN) may not contain the details that essentially correspond to the characteristics of the generated image. [A1]
- **The high calculation cost.** In CGAN, in addition to learning the distribution of generated images as unconditional GAN, the relationship between input conditions and generated images should also be learned, which further aggravates the burden of the model. Therefore, from this perspective, it is necessary to reduce the complexity of the model. One possible approach to this problem is model compression. However, the current research on how to implement model compression for CGAN is still very preliminary. For example, [105] only reduces the capacity of the model by screening the convolution kernel, which plays a rather limited role actually.

9. Minor corrections to the style of writing are necessary, as it is sometimes informal (for example, instead of "another big contribution", "another major contribution" should be used)

Response: Thanks for your comments very much. We have revised it and checked the whole paper to make this article more formal.