**Generating Publicity about our Business:**

1. **Write Positioning Statement** – Sums up what makes your business different from the competition
2. **List your objectives** – What do you hope to achieve for your company through the publicity plan you put into action? List your top five goals in order of priority. Be specific, and always set deadlines. Using a clothing boutique as an example, some goals may be to:
   1. increase your store traffic, which will translate into increased sales
   2. create a high profile for your store within the community
3. **Identify your target customers** – Are they male or female? What is the age range? What are their lifestyle, income and buying habits? Where do they live?
4. **Identify your target media** - List the newspapers and TV and radio programs in your area that would be appropriate outlets. Make a complete list of the media you want to target, then call them and ask whom you should contact regarding your area of business. Identify the specific reporter or producer who covers your area so you can contact them directly. Your local library will have media reference books that list contact names and numbers. Make your own media directory, listing names, addresses, and telephone numbers. Separate TV, radio and print sources. Know the "beats" covered by different reporters so you can be sure you are pitching your ideas to the appropriate person.
5. In this section we provide a brief overview of Condi- tional Random Fields (CRF) for pixel-wise labelling and introduce the notation used in the paper. A CRF, used in the context of pixel-wise label prediction, models pixel la- bels as random variables that form a Markov Random Field (MRF) when conditioned upon a global observation. The global observation is usually taken to be the image.
6. Minimizing the above CRF energy *E*(**x**) yields the most probable label assignment **x** for the given image. Since this exact minimization is intractable, a mean-field approxima- tion to the CRF distribution is used for approximate max- imum posterior marginal inference. It consists in approxi- mating the CRF distribution *P* (**X**) by a simpler distribution *Q*(**X**), which can be written as the product of independent marginal distributions, i.e., *Q*(**X**) = *i Qi*(*Xi*). The steps of the iterative algorithm for approximate mean-field infer- ence and its reformulation as an RNN are discussed next.

Convolutional networks are the de-facto standard for an- alyzing spatio-temporal data such as images, videos, and 3D shapes. Whilst some of this data is naturally dense (e.g., photos), many other data sources are inherently sparse. Examples include 3D point clouds that were ob- tained using a LiDAR scanner or RGB-D camera. Stan- dard “dense” implementations of convolutional networks are very inefficient when applied on such sparse data. We introduce new sparse convolutional operations that are de- signed to process spatially-sparse data more efficiently, and use them to develop spatially-sparse convolutional networks. We demonstrate the strong performance of the resulting models, called submanifold sparse convolutional networks (SSCNs), on two tasks involving semantic seg- mentation of 3D point clouds. In particular, our models outperform all prior state-of-the-art on the test set of a re- cent semantic segmentation competition.

Prior work on sparse convolutions implements a convo- lutional operator that increases the number of active sites with each layer [[3](file:///C:\MyData\Shankar\Technical\Python\Plagiarism\1711.10275v1-converted.docx#_bookmark31),4]. In [4], all sites that have at least one “active” input site are considered as active. In [[3](file:///C:\MyData\Shankar\Technical\Python\Plagiarism\1711.10275v1-converted.docx#_bookmark31)], a greater degree of sparsity is attained *after* the convolution has been calculated by using ReLUs and a special loss function. In contrast, we introduce *submanifold* sparse convolutions that fix the location of active sites so that the sparsity remains unchanged for many layers. We show that this makes it practical to train deep and efficient net- works similar to VGG networks [[20](file:///C:\MyData\Shankar\Technical\Python\Plagiarism\1711.10275v1-converted.docx#_bookmark48)] or ResNets [[7](file:///C:\MyData\Shankar\Technical\Python\Plagiarism\1711.10275v1-converted.docx#_bookmark35)], and that it is well suited for the task of point-wise semantic segmentation.

Photo-realistic image rendering using standard graphics techniques is involved, since geometry, materials, and light transport must be simulated explicitly. Although existing graphics algorithms excel at the task, building and edit- ing virtual environments is expensive and time-consuming. That is because we have to model every aspect of the world explicitly. If we were able to render photo-realistic images using a model learned from data, we could turn the process of graphics rendering into a model learning and inference problem. Then, we could simplify the process of creating new virtual worlds by training models on new datasets. We could even make it easier to customize environments by al- lowing users to simply specify overall semantic structure rather than modeling geometry, materials, or lighting.

Furthermore, to support interactive semantic manipula- tion, we extend our method in two directions. First, we use instance-level object segmentation information, which can separate different object instances within the same cat- egory. This enables flexible object manipulations, such as adding/removing objects and changing object types. Sec- ond, we propose a method to generate diverse results given the same input label map, allowing the user to edit the ap- pearance of the same object interactively.

We compare against state-of-the-art visual synthesis sys- tems [[5](file:///C:\MyData\Shankar\Technical\Python\Plagiarism\1711.11585v2-converted.docx#_bookmark44),[21](file:///C:\MyData\Shankar\Technical\Python\Plagiarism\1711.11585v2-converted.docx#_bookmark60)], and show that our method outperforms these approaches regarding both quantitative evaluations and hu- man perception studies. We also perform an ablation study regarding the training objectives and the importance of instance-level segmentation information. In addition to se- mantic manipulation, we test our method on edge2photo ap- plications (Figs.2[,](file:///C:\MyData\Shankar\Technical\Python\Plagiarism\1711.11585v2-converted.docx#_bookmark3)[13](file:///C:\MyData\Shankar\Technical\Python\Plagiarism\1711.11585v2-converted.docx#_bookmark39)), which shows the generalizability of our approach. Code and data are available at our[website](https://tcwang0509.github.io/pix2pixHD/)

**What is our Pitch?**

**For Businesses:**

* Save money through digitization
* Connect businesses with their customers directly, every time a document is uploaded by a business for a customer’s transaction
* Collect and share “Word-of-mouth” recommendations about their businesses / services to their connections’ connections
* Build Brand and online presence
* Retain and Enhance customer loyalty and customer base
* Cross-sell allied products / services (warranty, AMC, warranty / AMC renewals, DVD players for TV, …)
* Reminders for timely services – Automobiles, Insurance, …
* Emotional value – Save environment

**For Consumers:**

* Digitize documents, reduce clutter, avoid printing and Save environment
* Invite friends & family, build your own community of trust, share digital
* Only one copy of the digital document to avoid
* Manage documents centrally – one stop storage of all documents (invoices, warranty, user manual, insurance, …)
* Access from anywhere anytime using a device of choice – Cloud enabled; web and mobile apps
* Never miss any critical actions – warrant renewals, timely service of the devices / automobiles, insurance payments, …
* Connect directly with businesses
* Build your own community of trust, leverage the recommendations from trusted connections while making important decisions (buy / sell …)